Simulation-based Analysis of Product Costing Systems and Errors in Product Cost Information

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SUMMARY

This thesis examines how errors in product costing systems arise and cause distorted product costs. Accurate information about product costs is essential for a firm's long-term profitability because inaccuracies in product cost information can lead to suboptimal cost-based decisions, such as pricing or resource allocation. To obtain accurate product costs, firms are required to measure all products' resource consumptions accurately and link these to the cost-evoking products. However, due to the complexity of firms' resource consumption this is economically too effortful. Therefore, firms design and employ costing systems that approximate the underlying resource consumption to allocate costs to products. The costing system design balances implementation and maintenance efforts with the costs and consequences of inaccurate product cost information. To overcome the challenge of this trade-off, firms require an understanding of how errors in cost information arise. This can help answering questions, such as where refining a costing system likely pays off or which products are potentially over- or undercosted. This thesis summarizes recurring observations from prior studies regarding errors in product cost information to provide the current understanding of how these errors arise and manifest in different products' costs. From there, two prominent simulation models from this literature are replicated to test the internal validity of their results and recommendations concerning errors in product costs. Based on successful replications, an Activity-Based Costing (ABC) hierarchy, derived from the empirical and theoretical literature, is implemented into the models to examine their results' external validity toward this change in underlying resource consumption. More specifically, this extension tests the robustness of costing system design rules and the widely shared pattern of volume-based costing (VBC) cross-subsidization. Lastly, this thesis examines the emergence and mechanism behind errors in single product costs as opposed to the whole portfolio of a firm to determine which products are usually under- or overcosted. Overall, the results contribute to the literature on costing system design and cost accounting by expanding the understanding of how errors in product cost information arise, which refinements of a costing system reduce errors, and how errors distribute to single products. This provides practical guidance for managers designing a costing system or making decisions based on reported product costs.

CONTENT

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS AND SYMBOLS

ABC	Activity-based costing
ABM	Agent-based model
ABL	Anand, Balakrishnan and Labro (2019)
ACT_CONS_PAT	Activity consumption matrix
AE	Aggregation error
AMT	Advanced manufacturing technology
APE	Absolute percentage error
BE_AB	Difference in undercosting and overcosting
BHL	Balakrishnan, Hansen, and Labro (2011)
bl_size	Size of batch-level costs/resources
CC	Correlation cut-off threshold
CD-Heuristic	Heuristic for cost driver selection
consBigDriver	Relative consumption of large cost drivers
COR	Correlation between volume and batch-level resources
COR1	Correlation for volume/unit-level resources
COR2	Correlation for batch/non-unit-level resources
CP	Cost pools
CP-Heuristic	Heuristic for post pool building
CSD	Costing system design
DENS	Degree of resource sharing
DISP1	Number of “big” resources
DISP2	Share of costs for “big” resources
EOQ	Economic order quantity
ERP	Enterprise resource planning
ErrorDisp	Disparity in error distribution
EUCD	Euclidean distance
fl_size	Size of facility-sustaining level costs/resources
KS-Test	Kolmogorov-Smirnov test
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MCS	Monte-Carlo simulation
ME	Measurement error
MISCPOOLSIZE	Relative share of costs in the miscellaneous cost pool
MOH	Manufacturing overhead
MonE	Monetary Error
MSE	Mean squared error
MXQ	Production quantity vector
Non_unit_size	Size of non-unit-level costs/resources
NumbDriver	Number of consumed drivers of a single product
NUMB_PRO	Number of products
NUMB_RES	Number of resources

NumbRes	Number of consumed resources of a single product
PCB	Benchmark costs of a cost object/product
PCH	Heuristics costs of a cost object/product
PE	Percentage error
PER_BATCH	Share of costs for batch-level resources
PLE	Product-level errors
pl_size	Size of product-sustaining level costs/resources
ProductVol	Production volume of a single product
Q_VAR	Variation in production quantities
R&D	Research and development
RC	Resource consumption
RCA	Resource consumption accounting
RC_VAR	Variation in resource costs
RES_CONS_PAT	Resource consumption pattern matrix
SE	Specification error
SLE	System-level errors
SG&A	Selling, general, and administrative expenses
TC	Total costs
TDABC	Time-driven activity-based costing
UCShare	Share of undercosted products
ul_size	Size of unit-level costs/resources
ULCostShare	Share of reported-unit-level costs of a single product
VBC	Volume-based costing
VB_PATTERN	Pattern of volume-based cost cross-subsidization

1 INTRODUCTION

1.1 RESEARCH MOTIVATION

This thesis examines the error in allocated product costs caused by limited information costing systems to guide cost-based decision-making and the effective design of costing systems.[1]

To obtain accurate costs of single products, total periodic costs must be assigned based on a cause-and-effect relationship to single products (Balakrishnan, Labro, & Sivaramakrishnan, 2012a). In other words, costs must be assigned to those products that cause them (Kaplan & Atkinson, 1998). Misestimation of this relationship leads to an overestimation of some products' costs and an underestimation of other products' costs (Cooper & Kaplan, 1991; Hilton, 2011). This affects price-setting (Homburg, Nasev, & Plank, 2018), capacity planning (Anand, Balakrishnan, & Gavirneni, 2023), and other cost-based decisions (Balakrishnan, Hansen, & Labro, 2011)[2]. For example, understating a product's costs can create a misleading impression of high margins and capacities being shifted from other profitable products. Consequently, erroneous information about product costs can affect a firm's long-term profitability (Anand, Balakrishnan, & Labro, 2017; Labro, 2019), because limited resources are used inefficiently (Krishnan, 2015).

Identifying the cause-and-effect relationship between costs and causing products distinguishes between direct costs that are easily traceable to each product (Horngren, Datar, & Rajan, 2015), and indirect costs, which's error-free assignment to causing products is economically infeasible due to high measurement efforts (Balakrishnan & Sivaramakrishnan, 2002; Dopuch, 1993; Labro, 2006a).

Therefore, firms design limited information costing systems that aggregate the infeasible measurement efforts to allocate indirect costs to products in a cost-effective manner (Kaplan & Cooper, 1998b). A single-best approach for cost allocation through a costing system does not exist (Labro, 2006a). Instead, firms must design a costing system that matches their operations to identify the cause-and-effect relationship between costs and products (Horngren et al., 2015). Designing and maintaining a costing system requires the identification of cost pools, the distribution of costs into cost pools, and the measurement of cost drivers (Cooper & Slagmulder, 1999; Horngren et al., 2015; Labro, 2006a). Although simplified, these tasks can infer profound efforts for a firm (Cooper & Kaplan, 1999; Cooper & Slagmulder, 1999).

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[1] I use the terms product costs and (product) cost information interchangeably throughout this thesis.

[2] Parts of this thesis abbreviate the citation of Balakrishnan, Hansen & Labro (2011) to "BHL".

In summary, firms are required to balance the costs of implementing and designing a costing system with the costs of suboptimal decision-making based on inaccurately allocated costs (Cooper & Kaplan, 1988b; Labro & Vanhoucke, 2007). Identifying an optimal balance to this trade-off is economically relevant yet challenging (Krishnan, 2015).

To address this, several prior studies investigated the mechanics of costing systems and antecedents and consequences of errors in product cost information (Brierley, 2008; Labro, 2019; Mertens, 2020). Despite these studies' usefulness, challenges regarding their results' internal and external validity and uncovered perspectives on errors in product cost information persist, limiting the current understanding of costing systems and errors in allocated costs.

1.2 PROBLEM STATEMENT AND RESEARCH OBJECTIVES

This thesis's overall objective and research agenda is to overview and extend the understanding of how errors in cost information arise through limited information costing systems and manifest into different products' costs. I divide the overall aim into five challenges and resulting objectives, which I elaborate on below. In short, this thesis aims to review prior findings in the research field of costing system design and errors in product cost information to form recurring observations into patterns of errors in product cost information. These patterns can describe common notions about how errors in products costs "usually" arise. Based on that, several numerical experiments are conducted along these patterns to test the internal and external validity of corresponding results and recommendations. The applied numerical experiments replicate prominent publications in the field of costing system design (Anand, Balakrishnan, & Labro, 2019; Balakrishnan et al., 2011) and apply robustness analyses to their results, hence also examining their validity. Lastly, additional experiments are conducted to open new perspectives on errors in product cost information. These analyses contribute to a refined and expanded understanding of product cost information errors. To achieve this, the challenges and objectives described below are addressed.

Due to the non-measurability of true product costs, research was required to identify a workaround to gain insights into errors in reported product costs (Labro, 2015). This resulted in a variety of approaches in prior studies, such as surveys (Hughes & Paulson Gjerde, 2003; Schoute, 2011), laboratory experiments (Cardinaels & Labro, 2008; Schuhmacher & Burkert, 2021), case-studies (Gupta, 1993; Rezaie, Ostadi, & Torabi, 2008), analytical-models and numerical examples (Datar & Gupta, 1994; Hwang, Evans, & Hegde, 1993) and simulation-models (Balakrishnan et al., 2011; Labro & Vanhoucke, 2007, 2008). These different approaches employ a wide range of measures and approximations of errors in product cost information (Labro & Vanhoucke, 2007), which lead to a broad yet shallow field of research with few comparable studies (Shields, 2015). This potentially affects the validity of these studies' results, as they are seldom replicated, wherefore unreproducible results are not identified (Basu & Park, 2014; Shields, 2015). Moreover, the multifaceted effects of inaccurate cost information concern various managerial domains, such as product development, capacity planning, or pricing (Tse, 2011), and are researched in different areas and distributed in the literature (Brierley, 2008). In summary, these factors contribute to a currently scattered field of knowledge regarding errors in reported product cost information. An overview of recurring observations, so-called patterns (Grimm et al., 2005), concerning errors in product cost information can support practice in designing effective costing systems and guide research to where more insights might be required. Therefore, I define the first objective of this thesis as follows.

[1] The first objective of this thesis is to provide an overview of current recurring observations (patterns) regarding errors in product cost information.

Simulation-based approaches emerged as a central methodology to research errors in product cost information (Anand et al., 2019). Simulation models allow to generate error-free true product costs by modeling the true resource consumption of products on which a model of a limited information costing system can be applied to compute the corresponding reported erroneous product costs (Labro, 2006a). Consequently, in simulation experiments, it is possible to compare true and reported product costs in a wide variety of scenarios (e.g., different costing system designs or production environments). This enables insights into general drivers of errors in product cost information (Labro & Vanhoucke, 2007). However, as a first step, researchers must operationalize the characteristics of the systems under investigation (i.e., resource consumption and costing systems) into software to conduct simulation experiments (Maria, 1997). This operationalization limits the internal validity of results from simulation models because they can be confounded by implementation specificities or computational limitations (Thiele & Grimm, 2015; Wilensky & Rand, 2007). Moreover, simulation models and corresponding experiments can appear as black boxes due to their potential complexity (Lorscheid, Heine, & Meyer, 2012). This impedes the results reporting and challenges a common understanding of the underlying models, which in turn contributes to the above challenge of incomparability and validity of findings (Labro, 2015). In total, two main simulation models and frameworks emerged in the literature on errors in product cost information – the model from Anand et al. (2019) and the model in Balakrishnan et al. (2011). A replication of these two models based on best practices of model replication can support identifying results independent of confounding factors caused by the models' implementation.

This can highlight a higher internal validity of corresponding results, which is important for further research and theory building (Hauke, Achter, & Meyer, 2020). A successful replication can also emphasize that the two models are suitable frameworks for further research on costing system design.

[2] The second objective of this thesis is to replicate the two most prominent simulation models regarding errors in product cost information by applying best practices of model replication to scrutinize the internal validity of corresponding results.

In addition to the limitations of internal validity that arise by operationalizing a model into a software environment, limitations regarding external validity arise due to simplifying assumptions about the modeled systems (i.e., resource consumption and costing system design). Simplifying assumptions have to be made because the systems under investigation are too complex for direct analyses and must be reduced to the components relevant to answering the research objective (Maria, 1997; Robinson, 2008a). The assumptions are usually based on underlying theories or prevalent observations of the systems under investigation (Robinson, 2008b) and can significantly influence the results of the simulation experiments (Grimm & Berger, 2016a; Schmidt, Mertens, & Meyer, 2023; Thiele & Grimm, 2015). The simulation models that investigate errors in cost information (Anand et al., 2019; Balakrishnan et al., 2011) make several critical assumptions, one of which is how different products consume indirect resources. More precisely, the studies assume that products consume resources and costs in two different consumption patterns, which can be positively or negatively correlated with a product's production quantities (Balakrishnan et al., 2011). In contrast, a large body of literature suggests that resource consumption is separated more heterogeneously into four tiers of resource consumption patterns with different correlations and sizes of the single tiers (Anderson & Sedatole, 2013). This four-tier resource consumption is framed as the activity-based costing (ABC) cost hierarchy and is often mentioned as a major driver for the development of more sophisticated costing systems such as ABC (Cooper & Kaplan, 1991; Mertens, 2020). Simpler traditional volume-based costing systems (VBC) were expected to distort reported costs when resources are consumed, as assumed by the ABC cost hierarchy. Despite these relevant effects on errors in cost information, the ABC cost hierarchy has not yet been implemented into simulation models. This would allow testing and improving the external validity of costing system design rules and prior observations regarding errors in cost information toward this change. This includes practically relevant design heuristics from Balakrishnan et al. (2011) as well as suggested patterns, such as the observation that the majority of products within a portfolio are undercosted (Gupta, 1993; Labro & Vanhoucke, 2007).

[3] The third objective of this thesis is to examine the external validity of results from the two most prominent simulation models toward an ABC cost hierarchy.

Due to the missing examination of an ABC cost hierarchy on errors in product cost information, the mechanism behind the pattern of product cost cross-subsidization in VBC systems has not been extensively examined. More specifically, limited numerical examples (Shank & Govindarajan, 1988) and conceptual studies (Cooper & Kaplan, 1988b) noted that VBC systems undercost low-volume products and overcost high-volume products. This has contributed to an understanding that VBC systems are inferior to ABC systems (Mertens & Meyer, 2016). However, despite the wide recognition of the pattern of product cost cross-subsidization in VBC systems, the evidence is limited to exemplary and conceptual references (Schmidt et al., 2023). A detailed understanding of the mechanism behind the pattern can aid in identifying when the pattern is present and affects reported cost information. This would support practice and cost-based decision-making, as it warns managers when reported costs of certain products (i.e., high-volume or low-volume) are particularly distorted and should be used cautiously. Additionally, it would add to the discussion of the superiority of ABC over VBC (Gosselin, 2006).

[4] The fourth objective of this thesis is to investigate the mechanism behind the pattern of product cost cross-subsidization in VBC systems.

As already mentioned, the core requirement for costing systems is to facilitate cost-based decision-making by reporting accurate product costs (Labro, 2019). Despite this requirement, prior studies have primarily focused on assessing the overall error in reported costs for a whole portfolio (i.e., system-level error). This is a helpful angle to evaluate the design of a costing system (Labro & Vanhoucke, 2007) but it provides little insight into which products are usually overcosted and which are usually undercosted by a given costing system (i.e., product-level error). Findings regarding the product-level error and how the system-level error distributes across single products in the portfolio are scarce. However, cost-based decisions for single products are often based on single products’ costs (Anand et al., 2017). Consequently, product-specific costing errors are potentially the more relevant measure for examining the decision-influencing effect of product cost information errors.

[5] The fifth objective of this thesis is to investigate the errors in product cost information of single products as opposed to the whole portfolio to determine which products are usually under- or overcosted.

In summary, this thesis derives patterns of prior findings in the research field of costing system design and errors in product cost information and tests the internal and external validity of corresponding results through replication and robustness analyses. In addition to newly opened perspectives (e.g., product-level error), the understanding of how errors in cost allocation arise and manifest in different products' costs is expanded.

1.3 STRUCTURE OF THE THESIS

This thesis consists of five main chapters. Chapter 1 describes the overall objective of this thesis. In Chapter 2, I will provide the theoretical framework required for the forthcoming simulation analyses. The general structure and functionality of product costing systems will be described, and the current knowledge about resource consumption and cost behavior will be reviewed to provide a theoretical overview of how errors in cost information arise and diffuse through the costing system. Additionally, I will provide a methodological foundation for simulation and modeling approaches, along with model replication and robustness analysis tasks. These are the main methods developed and applied in this thesis.

Chapter 3 will derive currently known patterns of errors in product cost information that emerge from different studies and research domains. This overview will help to categorize the conducted analyses and findings of this thesis into the current field of research.

Chapter 4 will replicate the model from Balakrishnan et al. (2011) and test the provided costing system design heuristics' robustness toward an ABC cost hierarchy. Additionally, Chapter 4 examines the marginal benefits of reducing errors in product cost information when refining the costing system.

In Chapter 5, I will first replicate and then extend the model from Anand et al. (2019) by implementing an empirically derived ABC cost hierarchy into its resource consumption. I will develop and apply a best practice approach to model replication that employs priorly observed patterns to assess replication success. The extension will implement a four-tier ABC cost hierarchy and a VBC system into the model and examine the mechanism behind the product-cost cross-subsidization pattern of VBC systems.

Chapter 6 investigates how the system-level error distributes along single products in the portfolio and whether observable product characteristics signal a product's probability of being under-or overcosted by the costing system.

Finally, Chapter 7 revisits the identified patterns from Chapter 3 and summarizes the key findings of this thesis to each pattern. Additionally, it describes the limitations of the current modeling approaches in this thesis, provides potential directions for future research, and concludes this thesis.

2 THEORETICAL FOUNDATIONS

2.1 PRODUCT COSTING SYSTEMS

Product costs provide information about the total amount of costs that are assigned to a specific product (or cost object) [3] (Horngren et al., 2015). Thus, they are the basis for several managerial decisions, such as pricing (Banker & Hughes, 1994), product mix decisions (Anand et al., 2017) or capacity planning (Dierynck & Labro, 2018b). Collectively, accurate product costs are essential for a firm's economic success (Demski, 2008) because they link total costs with sold products and units (Hilton, 2011) and thus aid in the efficient and effective usage of limited resources (Krishnan, 2015). This linkage is obtained by identifying which costs are caused by a specific product. Here, cost accounting distinguishes between direct and indirect costs. Direct costs can be traced to individual products and measured without error (Hwang et al., 1993; Labro & Vanhoucke, 2007). Indirect costs cannot be traced directly to individual products in an economically feasible way (Horngren et al., 2015) because multiple products share the causing resources and activities, and the individual consumption for a single product is difficult to obtain (Balakrishnan & Sivaramakrishnan, 2002). For instance, electricity costs in a manufacturing plant that produces multiple products can be considered indirect because measuring how much electricity a single product consumes is difficult. Hence, firms employ product costing systems that use approximative measures to separate resource consumption for individual products and therein to allocate indirect costs without causing too high measurement efforts (Balakrishnan et al., 2012a). In the above example, the number of produced units can be employed as an approximation to allocate electricity costs to different products.

Several different types of product costing systems exist in the cost accounting literature and practice (Horngren et al., 2015). Balakrishnan et al. (2012a) and Balakrishnan, Labro, and Sivaramakrishnan (2012b) provide an overview and comparison of different product costing systems. Among others, traditional Volume-Based costing systems (VBC) and Activity-Based costing systems (ABC) are the most common product costing system designs (Al-Omiri & Drury, 2007; Drury & Tayles, 1994, 2005). Despite their differences in some aspects, many costing systems share standard functionalities.

More precisely, to allocate indirect costs to products, product costing systems usually follow a two-stage allocation procedure (see Figure 1) (Labro, 2006a). In the first stage (1), costs from resources are grouped into resource cost pools. Resource costs are usually taken from financial

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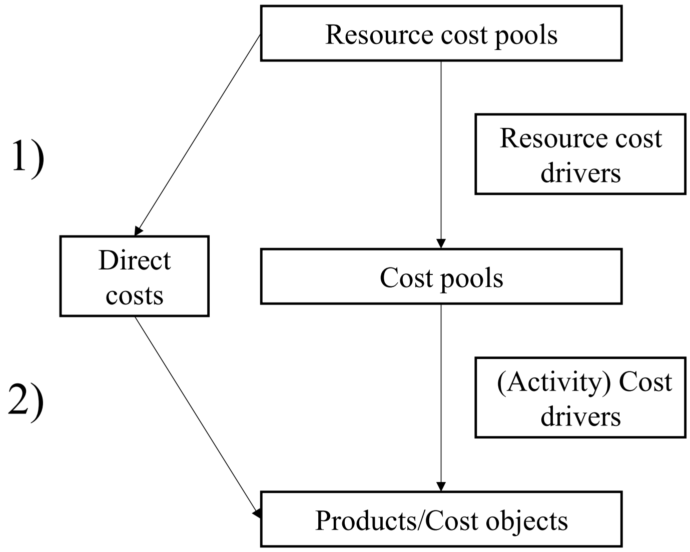
[3] Cost objects are not necessarily final products but can also be services, unfinished products or components (Balakrishnan et al., 2012a). This thesis employs the terms products, services and cost objects interchangeably.

accounting and refer to the overall expenses of the considered period for that resource (Balakrishnan et al., 2011; Balakrishnan et al., 2012a). Grouping these single resources' costs into resource cost pools allows for a simplified overview of a firm's costs (Labro & Vanhoucke, 2007). Generally, similar resources are grouped so that a resource cost pool reflects a homogeneous resource consumption (Noreen, 1991), such as labor, administrative, or material costs. Similar to the resource costs, the resulting resource cost pools can also be separated into direct and indirect resource cost pools (Horngren et al., 2015).

Figure 1. Two-stage allocation procedure in product costing systems adapted from Mertens (2020) and Labro and Vanhoucke (2007)



In the second stage (2), the indirect resource cost pools are further allocated to (Activity) cost pools by employing systematic rules to assign fractions of a cost pool to their causing activities or operations (Hilton, 2011). Such systematic rules again differ, depending on the information availability for the costing system and the exerted effort in designing and implementing the costing system (Balakrishnan et al., 2011). For instance, ABC employs performed activities in the firm's operations as the allocation base for an activity cost pool. Simpler costing system designs, such as VBC, solely focus on easily measurable unit-level activities or even production volume as the allocation base for a cost pool (Shank & Govindarajan, 1988).

2.2 COSTING SYSTEM DESIGN AND ACCURACY

Although the general two-stage allocation process of costing systems remains a common basis for most costing systems, they can differ in various choices in the design of costing systems (Balakrishnan et al., 2011; Balakrishnan et al., 2012a; Drury & Tayles, 2005). These choices are made by the implementing firm or costing system designer (Hilton, 2011) and determine the degree of sophistication and information demand of the costing system. The firm faces a trade-off between the required implementation efforts and a more sophisticated costing system (Cooper, 1989).

More sophisticated costing systems usually result in more accurately reported product costs (Balakrishnan et al., 2011), which is one of the most important criteria for costing system design (Pavlatos & Paggios, 2009; Pizzini, 2006) because many managerial decisions are based on reported product costs (Coller & Collini, 2014; Innes & Mitchell, 1995). In fact, several studies investigate the effect of errors in product cost information on decision-making efficacy and find a mainly positive relation to accuracy in reported product costs. For instance, Banker and Potter (1993) are the first to analytically show that multiple cost driver costing systems report more accurate product costs and improve a firm's performance in most scenarios. Moriarity (2005) and Gupta and King (1997) employ experimental settings and show that study participants make improved product mix decisions when product costs are reported more accurately. Anand et al. (2017), Coller and Collini (2014), and Homburg et al. (2018) employ different simulation models, and all find a similar link between costing system sophistication, reported product cost accuracy, and decision-making efficacy.[4]

Contrarily, more sophisticated and more accurate costing systems are usually more information-demanding and require greater implementation efforts (Duh et al., 2009; Roztocki et al., 2004), such as measuring the resource consumption of individual activities or resources (Cardinaels & Labro, 2008) or identifying relations between different resources to create homogeneous cost pools and select appropriate cost drivers (Banker & Johnston, 1993; Foster & Gupta, 1990). Hence, the benefits of costing system design choices regarding accuracy must be weighed against their implementation efforts. To understand when and how a different costing system design choice pays off, it is required to understand (1) the possible costing system design choices a firm can make (Chapter 2.2.1) and (2) how costing systems introduce errors in reported product costs (Chapter 2.2.2).

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[4] On a different note, these studies often stress the limitations of their findings and highlight that there are several settings in which less accurate reported product costs can support optimal decision-making. In these settings, the distortions in product cost information introduced by the costing system align with the corresponding factor of the decision to be made (e.g., shifts in demand or price changes (Banker & Potter, 1993)). Additionally, inaccuracies in reported costs may even be knowingly introduced to stimulate employee behavior or guide managerial attention (Merchant & Shields, 1993).

2.2.1 COSTING SYSTEM DESIGN

The most important aspect of designing a costing system is the accuracy of reported product costs (Horngren et al., 2015; Pizzini, 2006). Therefore, many costing system design choices follow this objective (Pavlatos & Paggios, 2009).[5] Generally, three main design aspects for the costing system beyond the common two-stage allocation procedure exist (Labro, 2006a) - the number of cost pools[6], the algorithm for grouping (resource) costs into cost pools, and the selection of cost drivers.

The number of cost pools determines the degree of aggregation with which the costing system approximates the true resource consumption (Horngren et al., 2015). Traditional cost accounting approaches often only employ one overhead cost pool (Cooper & Kaplan, 1988b) in which all indirect costs are lumped together to be allocated via a single cost driver. For example, these cost pools sometimes have been called “Manufacturing Overhead – MOH” and were allocated based on production volumes of individual products (Cooper & Kaplan, 1999). Thus, the resource consumption of all indirect costs and resources is mirrored by one cost pool and its respective cost driver. Although, this costing system design is considered likely to introduce errors in reported product costs (Hwang et al., 1993) several surveys report that a significant fraction of firms still employ single-pool/driver costing systems (Al-Omiri & Drury, 2007; Brierley, Cowton, & Drury, 2001; Drury & Tayles, 1994, 2005; Innes & Mitchell, 1995) (see also Table 26). A reason for this can be that with fewer cost pools, fewer cost drives must be measured, which results in lower implementation or updating efforts of the costing system (Anand, Balakrishnan, & Labro, 2014; Horngren et al., 2015)

The selection of appropriate cost drivers sets the allocation bases on which indirect costs are allocated to individual products (Homburg, 2001). More importantly, as true resource consumption of indirect costs is empirically difficult to observe, the selected cost drivers determine the representation of how products consume resources (Mastilak, 2011). This affects both a managers understanding of indirect resource consumption (Booker, Drake, & Heitger,

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[5] As described in 2.2, increasing the accuracy of a costing system may not always be the primary objective of a costing system design. Firms may also use it to guiding employees’ attention (Chenhall, 2003; Merchant & Shields, 1993) or incentivizing innovation (Drake, Haka, & Ravenscroft, 1999). However, this thesis focuses on the decision improving aspect of more accurate reported costs.

[6] Other studies employ the term cost pool as a cost position or expenditure (e.g., from financial accounting; (Balakrishnan et al., 2012a)). This thesis defines a cost pool as an allocation base from which costs are then allocated to products and cost objects. Accordingly, one cost pool employs exactly one cost driver to achieve this (Labro, 2019).

2007) and the accuracy of reported product costs (Balakrishnan et al., 2011). Consequently, selecting cost drivers that approximate true resource consumption more accurately can reduce the demand for additional cost drivers and allocation bases. In other words, employing fewer and simpler yet accurate cost drivers reduces information acquisition costs (Homburg, 2001, 2005). A wide variety of types of cost drivers exist (Banker & Johnston, 2006) and are often separated into activity-based and volume-based cost drivers along the two most common types of costing systems, VBC and ABC (Fisher & Krumwiede, 2012; Labro, 2006a).

Additionally, other, less common costing system designs suggest different types of cost drivers. For instance, Time-Driven Activity-Based Costing (TDABC) employs time estimations as the allocation base (Kaplan & Anderson, 2003). Resource Consumption Accounting (RCA) further separates cost drivers into resource consumption that is related to production volume – variable costs – and resource consumption that is not – fixed costs (Balakrishnan et al., 2012a). Overall, simple cost drivers are usually easy-to-measure approximations of indirect resource consumption (Kaplan & Cooper, 1998b), such as production volumes or direct machine-hours (Horngren et al., 2015). Thus, VBC systems are considered to be less information-demanding than ABC systems because their employed cost drivers are easier to measure (Hilton, 2011; Kaplan & Atkinson, 1998). Complex cost drivers can be approximations more closely related to indirect resource consumption (Cokins, 2002), such as lines of code written for software development costs (Barb et al., 2014) or costs per engineering change of a product (Kaplan & Atkinson, 1998). These cost drivers combine multiple information into so-called composite or indexed cost drivers (Fremgen, 1981) to provide a more accurate measurement of the true resource consumption and are often employed in ABC systems (Al-Omiri & Drury, 2007).

Finally, grouping costs into cost pools determines the costs assigned to the respective cost driver. For instance, grouping resource costs into the cost pool “Product Design” defines that all these resource costs are allocated by the employed cost driver of the cost pool “Product Design” (Balakrishnan et al., 2011). Accordingly, the approach to grouping costs into cost pools can magnify the importance of cost driver selection (Labro & Vanhoucke, 2008) and interacts with the number of cost pools (Schmidt et al., 2023). The cost pool grouping aims to aggregate resource consumption so that fewer cost drivers must be measured (Homburg, 2005). Hence, the grouping ideally results in cost pools with homogeneous resource consumption (Horngren et al., 2015). Despite this importance, the literature on grouping costs into cost pools is sparse.[7] Balakrishnan et al. (2011) derive five methods for cost pool building from intuition and

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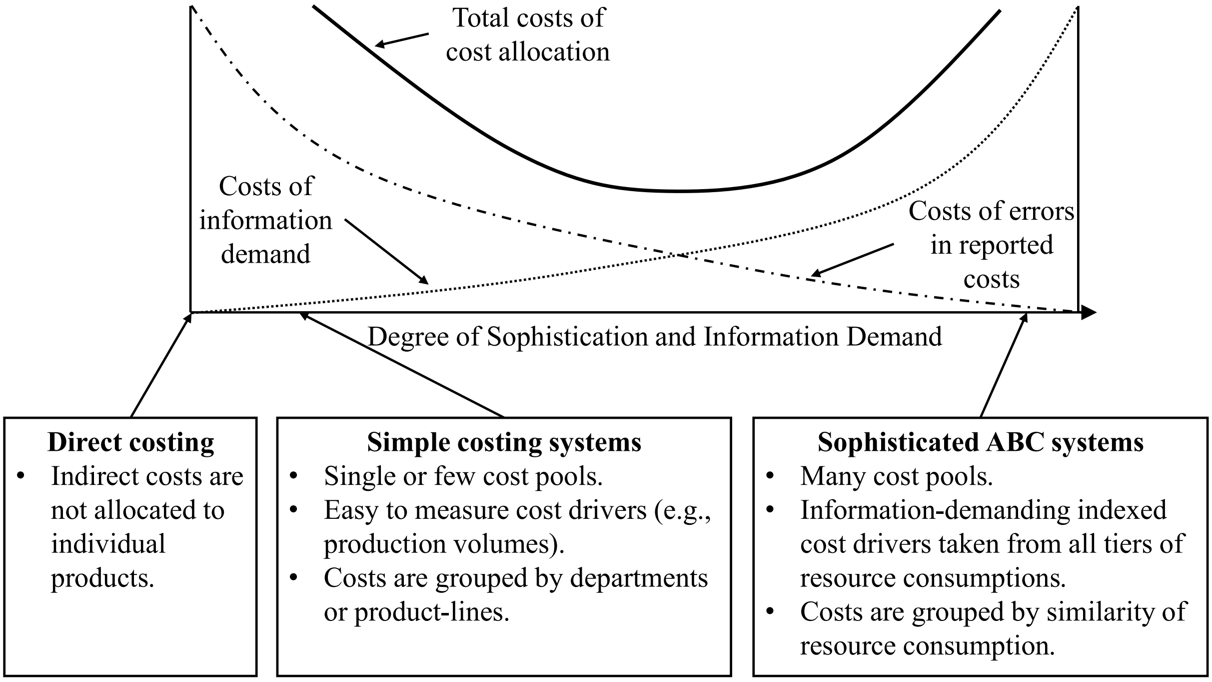
[7] Table 26 in Appendix 1 lists empirical observations of costing system designs and illustrates that reports on cost pool grouping are limited.

textbook guidance. For instance, they specify the “Willie-Sutton-Rule” (Kaplan & Cooper, 1998b) as to distribute expensive resources over different cost pools. Thus, high expenses are ideally recognized individually by the costing system and allocated more accurately (Anand et al., 2019; Gietzmann, 1991). Less expensive resources can be grouped based on their similarity to the large expenses in each cost pool or grouped into a miscellaneous cost pool (Balakrishnan et al., 2011). Grouping resources based on their similarity of resource consumption is considered more information-demanding (Meyer & Schmidt, 2024).

Collectively, the design decisions regarding number of cost pools, cost driver selection, and cost grouping determine the degree of sophistication and information demand of the costing system (Schoute, 2009a). As described above, more sophisticated costing systems are generally expected to provide more accurate product costs (Labro, 2019) but are also more costly to implement and maintain (Cooper, 1989). Figure 2 illustrates this trade-off and exemplary costing system design choices from direct costing (where indirect costs are not allocated to products) to simple costing systems (e.g., single cost driver costing systems) to sophisticated ABC systems.

Figure 2. Costs of costing system design



This trade-off is widely shared in the cost accounting literature, and similar depictions can be found in Cooper (1989); Kaplan and Atkinson (1998); Labro (2006a); Al-Omiri and Drury (2007); and Schoute (2009a). Based on the trade-off in Figure 2, an optimal costing system design minimizes the costs (or efforts) of information demand of the costing system with the costs of errors in reported product cost information resulting from suboptimal decision-making.

2.2.2 ERRORS IN COSTING SYSTEMS

As described, it is empirically too costly to measure all resource consumptions and therein allocate all indirect costs error-free to products (Dopuch, 1993). Instead, costing systems aim to provide a simplified approximation of the true resource consumption to obtain sufficiently accurate product costs (Labro, 2019). However, costing systems are rarely error-free (Noreen, 1991), because the simplification of the true resource consumption results in different types of errors in the cost allocation process (Labro & Vanhoucke, 2007). These errors within the costing system (e.g., from falsely obtaining true resource consumption) diffuse to individual products and result in errors in reported product cost information. Consequently, the costing system design, the true resource consumption, and their (dis-)alignment can be considered as the main driving factors of errors arising in the cost allocation process (see Figure 3).

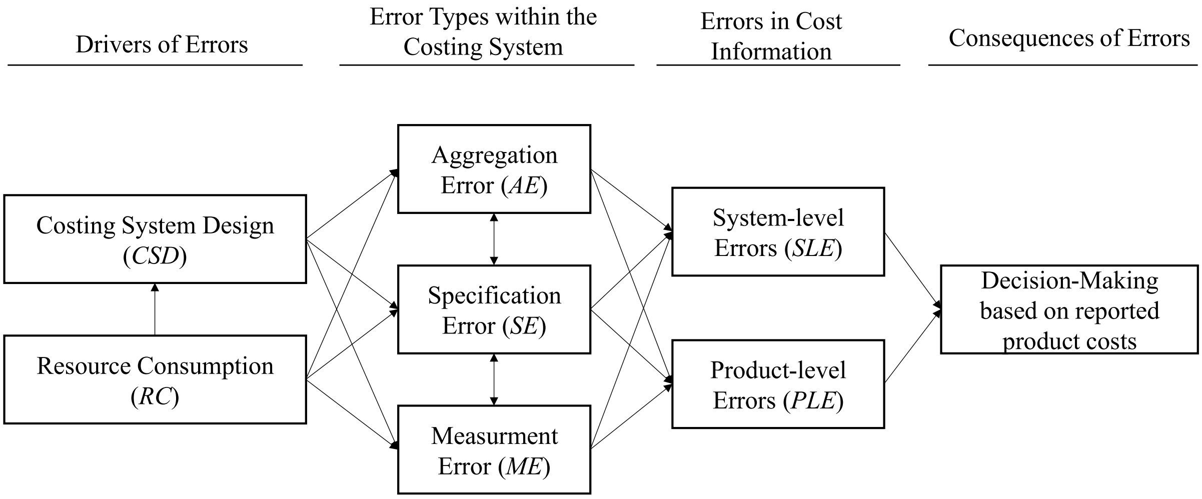
The different types of errors within cost allocation are generally separated into aggregation, specification, and measurement errors (Datar & Gupta, 1994). Aggregation errors arise when costs with different consumption patterns are grouped into one cost pool, wherefore an accurate allocation by a cost driver for that cost pool is no longer possible. For instance, costs for accounting activities and research and development efforts likely follow different consumption patterns, and grouping these together would result in aggregation errors.

Specification errors occur when the selected cost driver of a cost pool does not reflect its consumption pattern. Even though all resources' consumption patterns in a cost pool are homogeneous and correlate, the cost driver may reflect different consumption patterns. For example, a cost driver that employs direct-labor hours as the allocation rate for factory maintenance will likely introduce specification errors.

Lastly, measurement errors occur when the allocation rate of a cost driver is incorrectly measured or reported by the performing employee or department. An example of a measurement error is an over- or understating of the required time to perform a task or activity (Cardinaels & Labro, 2008).

Although these three error categories are widely shared and provide a straightforward understanding of errors in reported costs, the challenge arises as these three errors interact with each other (Labro & Vanhoucke, 2007, 2008). Reducing one type of error does not always yield a similar decrease in accuracy in reported product costs. Instead, it is even possible that different errors offset each other (Datar & Gupta, 1994), wherefore an incremental refinement of the costing system can reduce one type of error but increase another type of error, which results in an overall decreased accuracy (Labro & Vanhoucke, 2007). Figure 3 illustrates the conceptual relationship between different error types within the costing system, the errors in reported product costs, and their drivers and consequences for decision-making.

Figure 3. Conceptual overview of errors in costing systems



Although the different error types help to understand how distortions in reported product costs arise, the resulting errors in cost information can be assessed from different perspectives. Generally, errors ε in cost information of reported product costs arise as the difference between the true costs C_t and the reported costs C_r.[8]

$$C_r = C_t + \varepsilon$$

Assuming a firm that produces multiple products, two different types of errors can be assessed in reported cost information. First, the overall error of the costing system describes the deviation from true costs for a firm's whole product portfolio and is framed the *system-level error*. The system-level error is employed to evaluate the costing system overall (e.g., Balakrishnan et al., 2011; Labro & Vanhoucke, 2007, 2008). For this, errors ε of individual products are aggregated (e.g., averaged or summed) for the whole costing system.

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[8] For completeness, the overall error term ε can further be separated into the *bias* and *noise* in reported cost information C_r. In which *bias* is the a predictable difference between true and reported costs (Dierynck & Labro, 2018b), while *noise* is the random and unpredictable difference (Feltham & Xie, 1994). This thesis will focus on the overall error in reported costs and hence does not distinguish between noise in bias. Instead, the term bias is interchangeably with error and describes the direction of the error (i.e., product costs can be biased upward or downward).

However, errors in the product portfolio are likely not evenly distributed among individual products (Rezaie et al., 2008; Schmidt et al., 2023; Tuncel et al., 2005). Some products receive too many costs and are therein overcosted (i.e., positive ε) while others receive too little costs and are undercosted (i.e., negative ε). Since it is generally accepted that a firm's total costs are known (e.g. from financial accounting) (Balakrishnan et al., 2012a) , the sum of all errors ε for single products must be 0. Consequently, the individual product's costs cross-subsidize each other (Hilton, 2011), where the overcosted products carry the costs of other products that are undercosted (Labro, 2006a). The direction of this error (i.e., overcosting or undercosting) is often framed as the *bias* in reported product costs (Dierynck & Labro, 2018b; Labro, 2019; Mertens, 2020) and is different for every product (Mertens & Meyer, 2021). Some products' costs may contain large overcosting biases, while others are only slightly undercosted. The system-level error does not capture these product-level biases, wherefore a second perspective on errors in product cost information is required – the *product-level error* (Figure 3). The product-level error calculates errors in individual products' reported cost information. To obtain the different errors, several measures exist in the literature. Table 1 overviews these measures, their definitions, and references.

Table 1. Measures for errors in product cost information - Extended from Labro and Vanhoucke (2007)

Measure	Definition	References
System-level		
Euclidean Distance (*EUCD*)	$\sqrt{\sum_{i=1}^{CO}(C_t^i - C_r^i)^2}$	Babad and Balachandran (1993); Homburg (2001); Hwang et al. (1993); Balakrishnan et al. (2011); Coller and Collini (2014); Leitner (2012)
Mean Absolute Error (*MAE*)	$\frac{1}{CO}\sum_{i=1}^{CO}\lvert C_t^i - C_r^i\rvert$	N/A
Mean (Absolute) Percentage Error (*MPE/MAPE*)	$\frac{1}{CO}\sum_{i=1}^{CO}\left\lvert\frac{C_t^i - C_r^i}{C_t^i}\right\rvert$	Anand et al. (2019); Christensen and Demski (1997); Schmidt et al. (2023)
Mean Squared Error (*MSE*)	$\frac{1}{CO}\sum_{i=1}^{CO}(C_t^i - C_r^i)^2$	Datar and Gupta (1994)

Table 1 (continued).

Percent of accurate cost objects *(%ACC)* (10% error defined as immaterial)	$\frac{1}{CO}\sum_{i=1}^{CO}\{1 \| 0.95 * C_t^i < C_r^i < C_t^i * 1.05; 0\ otherwise\}$	Balakrishnan et al. (2011)
Product-level		
Percentage Error (*PE*)	$\frac{C_t^i - C_r^i}{C_t^i}$	Schmidt et al. (2023); Mertens and Meyer (2021)
Absolute Percentage Error (*APE*)	$\frac{\lvert C_t^i - C_r^i \rvert}{C_t^i}$	Mertens and Meyer (2021)
Monetary Error (*MonE*)	$C_t^i - C_r^i$	N/A

Note. CO = Number of cost objects/products; C_t^i = True costs of cost object *i;* C_r^i = Reported costs of cost object *i.*

The two most employed system-level error measures are the Euclidean Distance (*EUCD*), which measures the total value of misallocated costs (Balakrishnan et al., 2011), and the mean (absolute) percentage error (*MAPE*) (Anand et al., 2019), which measures the average percentage deviation between true and reported product costs. For the product-level error, the percentage error (*PE*) has been applied in prior studies (e.g., Schmidt et al., 2023), which measures the percentage deviation between true and reported costs for a single product. Relative error measures provide more information as they relate the error magnitude to the product costs (Labro & Vanhoucke, 2007). However, they can also appear misleading. For instance, a 10% error on a cost-wise small product is potentially less important than a 10% error on a cost-wise large product (Labro & Vanhoucke, 2007). Based on that, a costing system in which a large fraction of total costs is allocated correctly (i.e., low *EUCD*) may have a high *MAPE*, which stems from cost-wise small products. In contrast, it can be argued that absolute measures such as the *EUCD* depreciate high relative errors (i.e., high PE) for cost-wise smaller products and overemphasize errors in potentially few cost-wise large products.

Additionally, system-level measures (e.g., *EUCD* and *MAPE*) have the advantage of evaluating the accuracy of the whole costing system in one number. These measures are, therefore, beneficial to assess the effectiveness of costing system design heuristics or rules of thumb (Balakrishnan et al., 2011). Contrarily, they do not provide insights into biases within single product costs. Lastly, measures that employ the absolute deviation from true costs (e.g., *APE*) hide information about the direction of the error (i.e., under- or overcosting). Especially for product-level errors this can provide distorted insights. Overall, the measures address different challenges caused by errors in product cost information, such as costing system design or identifying high errors in single products’ costs.

2.3 RESOURCE CONSUMPTION[9]

The resource consumption of an individual product refers to the amount of a particular resource required to produce that product in the desired quantities (Anand et al., 2019). For instance, producing *one* bicycle variant has the direct resource consumption of two wheels and one frame and the resulting direct costs thereof (i.e., material costs). The machine's maintenance costs on which the frame and wheels are assembled would reflect indirect costs *if* the machine is shared with other bicycles produced by the firm. In that case, the consumption of the maintenance costs is too difficult to be directly traced to each bicycle variant. Consequently, to allocate the maintenance costs to individual products (e.g., different bicycles), the maintenance consumption is approximated by the costing system, for instance, by employing the number of produced units of each variant as the maintenance cost driver. Collectively, direct costs can be traced error-free to individual products (Hwang et al., 1993), whereas the consumption of indirect costs[10] by individual products must be approximated by the costing system (Balakrishnan & Sivaramakrishnan, 2002). However, indirect costs are consumed by every product individually, like direct costs.

The cost accounting literature distinguishes between two types of indirect costs – true and artificial indirect costs (Friedl, 2010). True indirect costs are consumed by every product in the same amount and are, hence, truly decoupled from individual products. Artificial indirect costs are consumed in different magnitudes (similar to direct costs) by individual products. Therefore, artificial indirect costs cause errors in cost allocation as they cannot be spread equally among all products of a firm’s portfolio like true indirect costs. Artificial indirect costs require sufficient approximation through the costing system (Horngren et al., 2015). There is an ongoing discussion about the ratios of true and artificial indirect costs in total overhead costs (Weber, 2022). A larger share of true indirect costs would reduce the need for sophisticated

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[9] Parts of this chapter are based on Schmidt, M., Mertens, K. G., & Meyer, M. (2023). Cost hierarchies and the pattern of product cost cross-subsidization: extending a computational model of costing system design. PLOS ONE, 18(9). doi: 10.1371/journal.pone.0290370 and Meyer, M., & Schmidt, M. (2024). Robust design heuristics for product costing systems: a replication and extension using an ABC cost hierarchy. Journal of Business Economics, Forthcoming.

[10] Other studies often frame indirect costs as “overhead” or manufacturing overhead “MOH” (Anderson, 1995; Anderson & Sedatole, 2013; Banker, Potter, & Srinivasan, 2021b).

cost allocation (Weber, 2022) because a large share of total indirect costs could be spread equally among all products (Cooper & Kaplan, 1988b). However, several empirical studies find variations in the consumption of indirect costs that differ from the variation in the consumption of direct costs (e.g., Banker & Johnston, 1993; Banker, Potter, & Schroeder, 1995; Datar et al., 1993; Foster & Gupta, 1990).[11] Consequently, artificial indirect costs are likely present in most firms and make up for a significant fraction of total costs.

How the resource consumption of artificial indirect costs varies is unique for every firm (Labro, 2019) and moreover differs along multiple environmental parameters, such as the employed production technology (e.g., Abernethy et al., 2001; Krumwiede, 1998), organizational structure (Al-Omiri & Drury, 2007; Drury & Tayles, 2005) or strategic orientation of the firm (Drury & Tayles, 1994, 2005). These parameters determine the heterogeneity of resource consumption, reflecting the extent to which products consume various resources or activities in differing patterns and magnitudes (Labro & Vanhoucke, 2008). This heterogeneity is often said to complicate the accurate approximation of true resource consumption by costing systems (Abernethy et al., 2001; Gupta, 1993).[12]

Cost accounting literature describes some common and recurring aspects of indirect resource consumption and resulting heterogeneity that help to understand how costing systems can approximate true resource consumption to reduce errors in reported product cost information.

Two fundamental conceptualizations exist in the cost accounting literature that aim to theorize the different consumption patterns of indirect costs (Anderson & Sedatole, 2013) – the *traditional cost hierarchy* and the *ABC cost hierarchy* (Kaplan & Atkinson, 1998). Both conceptualizations explain the behavior of indirect costs by relating the corresponding indirect resource consumption with direct resource consumption, such as production activities, direct labor, or machine hours (Banker & Johnston, 2006; Banker et al., 1995) to distinguish between different tiers of resource consumption (Kaplan & Atkinson, 1998) that, together, construct a cost hierarchy (Labro, 2004).

The traditional cost hierarchy assumes that consumption of indirect costs either varies proportionally with production volumes (i.e., variable costs) or is fully decoupled from

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[11] For simplicity reasons, this thesis uses the terms indirect costs and artificial indirect costs interchangeably, as artificial indirect costs are most relevant for cost allocation compared to true indirect costs.

[12] The concept of heterogeneity has multiple interpretations in the cost accounting literature and is often also called diversity in resource consumption (Labro & Vanhoucke, 2008) or product diversity (Abernethy et al., 2001). Gupta (1993) is the first to introduce the concept of differing consumption of indirect resources, which the costing system must approximate to compute accurate product costs. I follow his study and employ the term "heterogeneity".

production volume (i.e., fixed costs and true indirect costs) (Cooper & Kaplan, 1988b). Accordingly, this traditional volume-based approach separates indirect costs and corresponding resource consumption only into *two* tiers (Horngren et al., 2015). Hence, allocating indirect costs accurately to individual products only requires cost drivers that measure resource consumption that is highly correlated with the production of single units (Cooper & Kaplan, 1988b).

The ABC cost hierarchy assumes that indirect resource consumption not only varies with production volumes but with four different tiers of resource consumption – production volumes (unit-level), production batches (batch-level), variety of products produced (product-sustaining-level), and fully decoupled firm-wide resources (facility-sustaining-level) (Anderson & Sedatole, 2013; Cooper & Kaplan, 1988a, 1988b, 1991).[13] Batch-level costs occur with batches (i.e., groups of products) rather than single units produced (Horngren et al., 2015), such as the maintenance costs from the bicycle example. The consumption of product-sustaining-level costs varies along with the variety of products produced and the efforts of bringing the individual products to production (Fisher & Ittner, 1999), such as product design and development (Anderson, 1995). Finally, facility-sustaining-level resource consumption is completely decoupled from unit-level production activities. Thus, facility-sustaining-level costs can be considered true indirect costs (Kaplan & Atkinson, 1998). This, however, does not mean that all products consume these costs in the same magnitude. The rent of a facility is a typical example of facility-sustaining-level costs (Cooper & Kaplan, 1991). The production line of one product can take up most of the space of that facility. It may, therefore, be considered to consume a larger magnitude of these facility-sustaining-level costs, albeit the rental costs are entirely decoupled from the production volume.

There is an ongoing discussion about which of the two conceptualizations explains resource consumption of indirect costs more accurately (Anderson & Sedatole, 2013). Many firms still employ simple traditional costing systems (see Table 26). A firm's satisfaction with reported product costs from simple systems that represent the traditional cost hierarchy perspective (Anderson & Sedatole, 2013) can hint toward sufficient accuracy and an adequate approximation of the underlying resource consumption. In contrast, if the ABC cost hierarchy is more accurate, cost drivers that are also related to tiers other than unit-level resource consumption should better explain the variation of indirect resource consumption and costs (Banker et al., 2018). Indeed, Miller and Vollmann (1985), Cooper and Kaplan (1988a), Datar

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[13] The differentiation into these four tiers is the most prominent one in the cost accounting literature (Bloomfield, 2016), although other differentiations are possible as well (Banker & Johnston, 2006).

et al. (1993), Banker and Johnston (1993), Banker et al. (1995), and Anderson and Sedatole (2013) find that activity-based cost drivers better explain variations in indirect costs and their corresponding consumption. This substantiates that the *ABC cost hierarchy* may be the empirically more accurate conceptualization of resource consumption.

Several previous studies report on the properties and structure of empirically observed ABC cost hierarchies (Banker et al., 2021b). Generally, there are three dimensions in which the resource consumption within an ABC cost hierarchy can vary – (1) the degree to which resource consumption of different tiers correlates to each other, (2) the cost-wise size of the different tiers, and (3) the number of different resources within each tier.

The degree to which resource consumption of different tiers relates to each other, for instance, determines whether unit-level resource consumption is correlated with batch-level resource consumption. Batch-level costs show variations in activities related to batches, such as the number of batch setups or setup time (Anderson & Sedatole, 2013). According to the economic-order-quantity theory (EOQ), these costs are negatively related to production volumes (Misra, 1975). In other words, as production volumes increase, batch sizes also increase, reducing batch-level activities per production unit (Mertens, 2020). Consequently, batch-level resource consumption negatively correlates with unit-level resource consumption and production volume.

The consumption of resources at the product-sustaining level is associated with activities influenced by product variety, complexity, and related production processes, such as process design (Anderson & Sedatole, 2013; Cooper & Kaplan, 1991; Fisher & Ittner, 1999). Product-sustaining-level activities are expected to have a modest correlation with production quantities (Ittner, Larcker, & Randall, 1997), as these activities are connected to variable production influenced by the specific manufacturing technology employed (e.g., Advanced Manufacturing Technology vs. Workshop Production) (Schoute, 2011).

Facility-sustaining-level costs are, as described above, entirely decoupled from direct production activities and hence expected to be not correlated with unit-level resource consumption (Horngren et al., 2015). Contrarily, a correlation to product-sustaining-level resource consumption appears more likely, as increased product variety or design and development efforts result in more complex production facilities (Datar et al., 1993; Fisher & Ittner, 1999) and hence increased costs to sustain these facilities.

Table 2 illustrates empirically reported Pearson correlations between tiers in the lower diagonal cells and theoretically expected relations between the different tiers of the ABC cost hierarchy (-;0;+) in the upper diagonal cells. Overall, the empirical observations are inconclusive and display a wide range of observed positive, negative, and insignificant correlations. For instance, the correlation of resource consumption between unit-level and batch-level activities ranges from insignificant (e.g., 0.07 (Ittner et al., 1997)) to significantly high (e.g., 0.82** (Banker et al., 2021b)).

Table 2. Empirically observed and theoretically expected correlations between different tiers of the ABC cost hierarchy[14]

Tier/Tier	Unit-level	Batch-level	Product-sustaining-level	Facility-sustaining-level
Unit-level	1	-	0; +	0
Batch-level	**0.07** (Ittner et al., 1997) **0.02 – 0.82**** Banker et al. (2021b) **0.05 – 0.10** (Ittner & Macduffie, 1995)	1	0; -	0
Product-sustaining-level	**0.19** (Ittner et al., 1997) **0.43** – 0.78**** (Banker et al., 2021b)	**-0.41**** (Ittner et al., 1997) **0.30** - 0.93**** (Banker et al., 2021b) **0.12**** (Datar et al., 1993)	1	0
Facility-sustaining-level	**0.57*** (Banker et al., 1995) **0.08 – 0.20** (Ittner & Macduffie, 1995)	**0.28**** (Datar et al., 1993) **-0.17** (Banker et al., 1995) **-0.30** – 0.20** (Ittner & Macduffie, 1995)	**0.69**** (Datar et al., 1993) **0.44*** (Banker et al., 1995)	1

Note. * indicates p < .05. ** indicates p < .01 for the Pearson-Correlation, as found by the original studies.

The cost-wise size of the different tiers and the number of resources per tier determine which tiers are more critical to consider when pooling resources and selecting cost drivers (Cooper &

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[14] This table is based on a similar table published in Schmidt et al. (2023) and Meyer and Schmidt (2024).

Kaplan, 1999). For example, activities at the unit level might account for a large share of the total costs yet comprise a limited number of different tasks or resources utilized. This may be applicable in automated flow-shop production settings (Bloomfield, 2016), where few main production steps cause the most costs. In contrast, the facility-sustaining costs might represent a smaller portion of the total costs but involve a broader range of smaller resources or activities with different resource consumption patterns, such as facility management, rent, executive salaries (Mevellec, 2008).

Various elements influence these cost-to-number ratios of resources in the ABC cost hierarchy. For instance, past research indicates that the adoption of advanced manufacturing technologies (AMT) changes the pattern of resource usage, separating it from the volume of production and unit-level activities (Abernethy et al., 2001; Kerremans, Theunisse, & Van Overloop, 1991; Schoute, 2011). This shift likely causes an increase in either the number of resources and activities or the total costs incurred at non-unit-level tiers. As another example., studies in engineering suggest that enhancing modularity in products increases costs related to product development, impacting product-sustaining-level costs (Labro, 2004; Mertens et al., 2023) while concurrently reducing long-term unit-level costs (Fixson, 2006; Israelsen & Jørgensen, 2011). Table 3 presents empirical data on cost-wise size ratios and share of the different number of resources across various tiers in an ABC cost hierarchy.[15] While detailed ratios are limited to a few case studies and surveys, there is not always a direct correlation between cost-wise size and number of resources (for example, batch-level costs might make up 10.25% of the total, whereas batch-level resource share could account for 42%).

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[15] Table 3 also reports the averages across the observations. I employ these in Chapters 4 and 5 to implement an ABC cost hierarchy into the models.

Table 3. Empirically observed cost and resource ratios for the ABC cost hierarchy[16]

Cost share

	Total Indirect Costs				
		Non-Unit-level			Additional Information
Reference	Unit	Batch	Product	Facility	
(Cooper & Kaplan, 1991)	52%	22%	19%	7%	Case Study, N=1
(Hundal, 1997)	89%	2.4%	2.2%	5.7%	Case Study, N=1
(Al-Omiri & Drury, 2007)[2]	41%		59%		Survey, N=86
(Kallunki & Silvola, 2008)[1,2]	39.1%		60.9%		Survey, N=105
(Thyssen, Israelsen, & Jørgensen, 2006)[3]	81.6%	9%	9.4%		Case Study, N=1
(Gunasekaran & Singh, 1999)	23.4%	15.1%	27.2%	34.2%	Case Study, N=1
Average	**55.3%**	**12.40%**	**16.40%**	**15.29%**	

Resource share

	Total Number of Resources				
		Non-Unit-level			
Reference	Unit	Batch	Product	Facility	
(Duh et al., 2009)	54%	38%	-	8%	Case Study, N=1
(Ittner et al., 1997)[2]	42%		58%		Case Study, N=1
(Thyssen et al., 2006)[3]	28.5%	28.5%	43%		Case Study, N=1
(Gunasekaran & Singh, 1999)	21%	58%	7%	14%	Case Study, N=1
Average	**38%**	**43%**	**7.3%**	**11.7%**	

Note. [1] Values are normalized to add up to 100%, excluding direct costs, as in Mertens (2020). [2] Only unit-level and non-unit-level costs and resources are distinguished in the referenced study. [3] Product-sustaining and facility-sustaining costs and resources are grouped in the referenced study.

In summary, the ABC cost hierarchy imposes different resource consumption patterns for different resources in different tiers.

Overall, regardless of which cost hierarchy is assumed, the employed cost drivers must describe a relation between the driver of costs (e.g., the number of products produced) and the evoked resource consumption that is proportional to the actual relationship (Bloomfield, 2016). For this, cost accounting traditionally assumed a deterministic relationship between cost drivers and corresponding resource consumption (Banker et al., 2018). Thus, a change in the cost driver

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[16] This table is based on a similar table published in Schmidt et al. (2023) and Meyer and Schmidt (2024).

(e.g., increasing the production volume by one unit) results in a change in the underlying resource consumption (e.g., the additional consumption of one frame for a bicycle) (Noreen, 1991). This relationship can be linear or non-linear (Christensen & Demski, 1997; Labro, 2019; Noreen, 1991). Most prior studies investigate a Leontief production function that imposes a linear relationship between cost driver and costs (Demski, 2008). Non-linear relationships, such as in a Cobb-Douglas production function (Christensen & Demski, 1997) are potentially even more common in real-world systems (Christensen, 2010), but have not been modeled in many studies that investigate product costing systems (Labro, 2019). Notable exceptions are Dhavale (2007) and Christensen and Demski (1997).

Additionally, modern cost management research posits that managerial decisions influence this relationship (Banker & Byzalov, 2014), which results in asymmetric instead of symmetric cost behavior (Balakrishnan, Labro, & Soderstrom, 2014). As the most prominent instance of the phenomenon, Anderson, Banker, and Janakiraman (2003) observe that a decrease in the cost driver rate (e.g., production volumes) evokes a smaller decrease in selling, goods, and administrative costs compared to an increase in the cost driver rate. In other words, certain types of costs increase with greater magnitude than they decrease (Banker & Byzalov, 2014), which is framed as “cost-stickiness”. In this context, especially over the long term, cost behavior plays an essential role in cost allocation (Banker et al., 2018; Dhavale, 2007) and must be considered when constructing a costing system. Ibrahim, Ali, and Aboelkheir (2022) and Banker and Byzalov (2014) provide systematic overviews of drivers and determinants of asymmetric cost behavior.

To summarize, costs are caused by resource consumption. Understanding this resource consumption aids in allocating costs accurately to improve cost-based decision-making. Resource consumption is influenced by various factors and structured by the number of different resource tiers, how different tiers of resource consumption correlate with each other, what the cost-wise size of different tiers of resource consumption is, and how many different resources relate to different tiers. Most often, resource consumption is explained by either the traditional cost hierarchy or the ABC cost hierarchy (Banker & Johnston, 2006), where the ABC cost hierarchy is assumed to be more heterogeneous but potentially more realistic (Banker et al., 2021b).

2.4 MODELING AND SIMULATION

This thesis conducts computer simulation experiments as the central methodology to investigate product costing systems and errors in cost information. Computer simulation experiments provide two advantages relevant to the objective of this thesis. First, simulation experiments allow to incorporate a variety of settings and parameter combinations (Law & Kelton, 2007). This enables testing the generalizability of the system under investigation (e.g., a costing system) (Labro, 2015). Second, and more importantly, the simulation-based analysis allows to observe errors in cost information (Labro, 2006a), because empirically true costs of products can be modeled and contrasted with costs reported by a modeled costing system (Labro, 2006a). This comparison is too difficult for empirical methods (Balakrishnan & Sivaramakrishnan, 2002; Dopuch, 1993). As a result, simulation experiments are the primary methodology in previous research concerning product costing systems and errors in cost information (Grisar & Meyer, 2016; Labro, 2019).

Computer simulations or simulation experiments are mathematical models that virtually replicate real-world systems (Vallverdú, 2014). The mathematical models on which they are based are, in turn, simplified models of the exact system under investigation. Simulations are mainly employed when the considered mathematical model is too complex to be solved analytically (Frigg & Reiss, 2009). Mathematical models are formed when experiments with the exact system are impractical, and a physical model cannot reflect the desired properties. Thus, simulations are just one of several ways to investigate system characteristics.

Examining a system through simulation aims to better understand its properties and apply the resulting outcomes to reality (Law & Kelton, 2007; Reiss, 2011), ideally providing practical implications. A simulation experiment can have several objectives (Edmonds et al., 2019). Among the most prominent are – *explanation* (of the system under investigation) and *prediction* (of specific outcomes of the system) (Kleijnen, 1995; Law & Kelton, 2007). By observing changes in output parameters caused by the variation of input parameters or model structures, statements about the model's properties can be attributed to the system (Law & Kelton, 2007). For instance, in their simulation experiment, Balakrishnan et al. (2011) show that, on average, adding more cost pools to a costing system results in more accurate product costs. This positive relation between the number of cost pools and accuracy can be transferred into practice as a *prediction* for the system under investigation. Contrarily, by examining the mechanism behind an observed phenomenon, a simulation experiment can provide an *explanation* (Schmidt et al., 2023). For instance, in a prominent simulation study Reynolds (1987) showcases that the flying behavior for a flock of birds can traced back to three simple mechanisms – coherence, separation, and alignment. This simulation experiment supports explaining a system’s behavior rather than its prediction.

The increased computational power of computers in recent years has enabled simulations to model and solve ever more extensive and more complex systems (Küppers, 2006). Currently, simulations are applied in various research areas, including social sciences, bioinformatics, chemistry, particle physics, artificial intelligence, and economics (Wall, 2014), evolving into a fundamental scientific method (Vallverdú, 2014). Simulation models are instrumental in combination with analytical models, which, while more efficient, can be made more realistic using simulation models (Rand & Rust, 2011). Compared to analytical models, computer simulations, as applied in this thesis, are stochastic models instead of deterministic models (Maria, 1997). That means that comprehensive analytical solutions from deterministic models are approximated by randomly drawn numbers that cover realistic scenarios (Kleijnen, 1995; Law & Kelton, 2007) to generate insights about the system under investigation.

Different stochastic simulation methods address different objectives (Law & Kelton, 2007). For instance, among the most prominent methods in economics and management sciences are Agent-Based-Modeling (ABM) and Monte-Carlo Simulation (MCS) (Garcia, 2005; Grisar & Meyer, 2016; Wall, 2014). ABM focuses on the actions and rules of individual behaviors at a micro-level. This involves agents interacting with each other and their surroundings, leading to larger phenomena at the macro-level, like socio-technical or socio-ecological systems (Grimm et al., 2005), such as the flock of birds from Reynolds (1987). MCS uses repetition to explore uncertain input assumptions by generating various scenarios for analysis (Law & Kelton, 2007). MCS is often applied in risk management (Grisar & Meyer, 2016), where uncertainty about future events must be covered.[17]

The general approach to conduct simulation experiments is similar among the different simulation methods (Maria, 1997). The overall simulation model that is employed to conduct simulation experiments with consists of a conceptual model and a computer model (Kleijnen, 1995; Robinson, 2008a). The conceptual model represents the simplified version of the system under investigation reduced to relevant aspects to achieve the modeling objective (Kleijnen, 1995; Robinson, 2008a; Sargent, 1991). The conceptual model can be of any form and describes a system's model's goals, inputs, outputs, content, assumptions, and simplifications (Maria, 1997). The computer model is then the implementation of the conceptual model into a modeling software (e.g., programming language, such as Python or R) (Robinson, 2008a). Figure 4 illustrates this conceptual process of simulation modeling.

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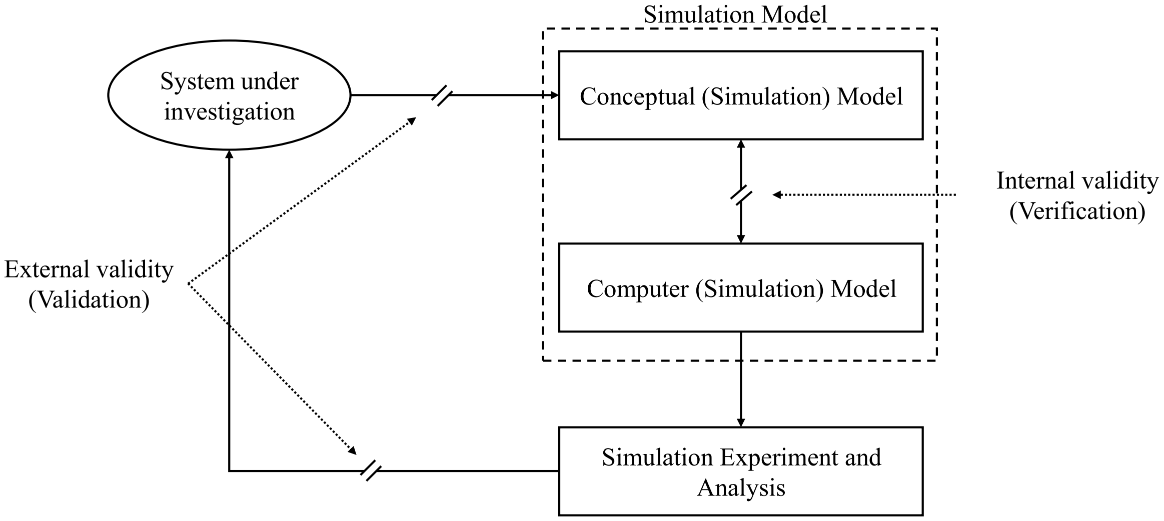
[17] The simulation methods applied in thesis primarily base on MCS as the different models do not focus on different agents and their interactions (Anand et al., 2019).

Figure 4. Process of simulation modeling



Although the application of simulation models to the study of complex systems offers several advantages, it also has disadvantages. As for other methods, the internal and external validity of results obtained from simulation experiments are at risk due to the characteristics of this method (Kleijnen, 1995).

External validity of results obtained from a (simulation) experiment refers to their ability to be generalized beyond the specific setting of the experiment (Libby, Bloomfield, & Nelson, 2002). External validity can be reduced for simulation models because the conceptual model fails to accurately represent the system under investigation (Law & Kelton, 2007). Thus, results are not transferable to the real-world system (Grimm & Berger, 2016b). This can arise because of the simplifications made in the modeling process (Kleijnen, 1995) or inappropriate selection of random number generation (Law & Kelton, 2007). Additionally, simulations and their results quickly become highly complex, making the analysis and presentation of results challenging (Grimm et al., 2005; Labro, 2015). These characteristics contribute to questioning the external validity of results from simulation experiments.

Internal validity of a simulation model describes the degree to which observed results are intended outcomes of the computer simulation and the corresponding experiment (Libby et al., 2002). More specifically, it ensures that no unwanted influences, such as implementation specificities, programming errors of the computer simulation (Maria, 1997), random number generators (Belding, 2000), choice of input variable distributions, and number of simulation runs (Kleijnen, 1995), affect the results.

Efforts can be made to increase the internal and external validity of simulation models' results (Sargent, 1991). The objective is to confirm that a considered system is "correctly" represented by the corresponding simulation model (Law & Kelton, 2007) and that it provides results that accurately explain the behavior of the system under investigation (see Figure 4). Higher external validity of a model is achieved through its validation and higher internal validity through its verification (Kleijnen, 1995). For both verification and validation, different approaches exist (Schmidt et al., 2023). A validation of a model can be conducted through a sensitivity analysis, comparison with analytical results, or real-world data (Kleijnen, 1995), or through a robustness analysis (Grimm & Berger, 2016a; Thiele & Grimm, 2015). A verification can be achieved through different types of model replication (Edmonds & Hales, 2003; Sargent, 2010; Wilensky & Rand, 2007). In summary, model replication and robustness analysis are highly relevant tools to ensure the validity of reported results from simulation models.

2.5 MODEL REPLICATION[18]

Model replication involves reimplementation of the computer model into a modeling software (e.g., programming language) that is distinct from the modeling software used for the original model (Sansores & Pavón, 2005). The reimplementation ideally relies on the conceptual model of the original simulation model. This approach aims to eliminate potential implementation and programming errors from the original model that could unintentionally affect the results (Wilensky & Rand, 2007). Implementation errors encompass misinterpretations of the conceptual model, including its theories or mathematical formalisms. Textual explanations in the model description may be insufficient, leading to diverse interpretations and implementations of the model. Additionally, programming errors ("bugs") may influence the results (Maria, 1997; Polhill, Izquierdo, & Gotts, 2004).

However, the feasibility of replication based solely on the conceptual model is challenged by divergences between conceptual and computer model (Burman, Reed, & Alm, 2010). Ambiguities in the writing or formalities of the conceptual model may hinder the replication solely from the conceptual model (Edmonds & Hales, 2003). More specifically, conceptual models are often formalized in written text (Levinthal, 1997; Plähn et al., 2023), as conceptual illustrations (Bellora-Bienengräber, Harten, & Meyer, 2023; Leitch, Philipoom, & Fry, 2005), or as pseudo-code (Anand et al., 2019). All these approaches can leave room for interpretations regarding the actual implementation (i.e., computer model) (Axtell et al., 1996). In more extreme scenarios, a conceptual model might even contradict the actual computer model

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[18] This chapter is loosely based and adapted from the appendix S1 in Schmidt, M, et al. (2023). "Cost hierarchies and the pattern of product cost cross-subsidization: extending a computational model of costing system design." PLOS ONE 18(9). The appendix can be retrieved from https://doi.org/10.1371/journal.pone.0290370.s002.

(e.g.,Will & Hegselmann, 2008). For instance, mathematical formalisms may lack convergence between the conceptual model and the code. Therefore, it is imperative to identify and document ambiguities and contradictions during the replication process (Schmidt et al., 2023). Overall, replication based on the conceptual model offers both challenges and possibilities for successful replication and an increase of a model's internal validity.

The replication success depends on comparing the replicated model with the original model against predefined criteria. Many models address specific research questions (Tivnan, 2007) and employ simulation experiments to answer these (Thiele & Grimm, 2015). Thus, replication success is contingent upon the production of identical results by both the replicated and original model (Axtell et al., 1996). To determine this, the relevant results that are the basis for comparison and the criteria that defines when results from both models are identical must be specified (Wilensky & Rand, 2007).

For simulation models that come with no particular results (e.g., Anand et al., 2019) or many results to select from, focusing on recurring patterns or stylized facts[19] of that research domain can provide an outlet on where replication success is most important (Grimm et al., 2005; Heine, Meyer, & Strangfeld, 2005; Meyer, 2019). These patterns are construed as descriptions of specific relations between input and output variables (Grimm & Berger, 2016a; Heine et al., 2005) and, therefore, enable testing through their similarity to traditional hypotheses.

To evaluate the replication success of the selected results, Axtell et al. (1996) propose three assessment criteria – relational, distributional, and numerical equivalence. These criteria, considered quasi-standard, have been employed in various replication studies (Edmonds & Hales, 2003; Meyer & Schmidt, 2024; Schmidt et al., 2023; Tivnan, 2007; Wilensky & Rand, 2007).

Relational equivalence refers to the qualitative reproduction of results, where both models qualitatively demonstrate the exact relations between input and output variables (Axelrod, 1997; Axtell et al., 1996). That means that the qualitative direction of a result is successfully reproduced but not its magnitude. Relational equivalence is, thus, the least demanding criterion for replication success (Schmidt et al., 2023).

Distributional equivalence requires statistically indistinguishable results from both models (Axtell et al., 1996). Standard statistical tests (e.g., t-tests or Kolmogorov-Smirnov tests)

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[19] Both terms, patterns and stylized facts refer to recurring observations of a specific phenomenon in different and independently observed systems (Grimm et al., 2005; Kaldor, 1961; Meyer, 2019). The term pattern primarily stems from and is used in ecological research while stylized facts are commonly employed in economic and management research (Meyer, 2019).

(Fachada et al., 2017) assess whether two sets of measures (e.g., relevant results from both models) can be drawn from the same distribution (Axelrod, 1997). Yet, traditional statistical tests are flawed toward large sample sizes, which are common in simulation studies (Secchi & Seri, 2017; White et al., 2014), and can report irrelevant divergences between the compared results as significant (Fachada et al., 2017).[20]

Finally, numerical equivalence necessitates that both models produce numerically identical results (Axtell et al., 1996). Achieving numerical equivalence is challenging in stochastic computational models due to random number variations and differences in generators (Maria, 1997). Pseudo-random numbers introduce systematic discrepancies in independent variables, especially with sufficient simulation runs (Belding, 2000).

In summary, the assessment of replication success through these criteria offers a comprehensive overview of whether a reimplementation in different software, ideally based on the conceptual model, can faithfully reproduce the original model's results. Thus, model replication enhances the internal validity of the computational model while ensuring the absence of programming and implementation specificities that could affect results.

2.6 MODEL ROBUSTNESS ANALYSIS

The robustness analysis of a simulation model is a widespread approach to increase the external validity of the results of the simulation model (Grimm & Berger, 2016a). Hence, it is often combined with a beforehand replication of a simulation model to increase the overall validity of the model’s results (Thiele & Grimm, 2015). It is often also referred to as a replication with extension (Hubbard & Armstrong, 1994). A robustness analysis generally involves a fundamental change to the structure and parameters of a simulation model and observes whether and how the results alter through this change (Grimm & Berger, 2016b).

A robustness analysis aims to elucidate the fundamental workings of a model to derive generalizable principles that extend beyond the model's boundaries — referred to as *robust theories* (Weisberg, 2006). To achieve this, a robustness analysis aims to separate so-called key mechanisms from those resulting from specific model properties (Levins, 1966). More specifically, a robustness analysis explores instances where the model is no longer capable of producing the original results (Weisberg, 2006), leading to the often-used term "model breaking" (e.g., Thiele & Grimm, 2015).

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[20] Figure 38 in the appendix illustrates this distortion in a Kolmogorov-Smirnov-test for increasing sample sizes.

Due to the diverse nature of simulation models, the specific modifications in a robustness analysis are not precisely defined. In most cases, the approach depends on the knowledge, objectives, and capacities of the conducting researcher (Grimm & Berger, 2016a). Consequently, various descriptions exist regarding the approaches to conducting a robustness analysis (Burman et al., 2010; Grimm & Berger, 2016a; Levins, 1966; Weisberg, 2006). This variability leads to criticism of a robustness analysis. Orzack and Sober (1993) argue that the lack of a uniform definition of the approach contributes to the fact that the robustness analysis is not a method for determining "*correct*" robust theories, according to the definition of Levins (1966). This implies that the comparison of models (i.e., original and modified simulation model) does not rule out the possibility that the identified robust theories inaccurately describe the modeled system (e.g., if all considered models are "*incorrect*," identified robust theories are likely to be incorrect as well) (Orzack & Sober, 1993). In the more recent simulation modeling literature Grimm and Berger (2016a) describe a possible approach to conduct a robustness analysis and propose four categories for modifying the original model to establish robust theorems.

1) Analysis of non-realistic scenarios: Certain model properties are approximated to non-realistic scenarios to highlight the functioning of other model properties.
2) Simplification of the model: One or more model components are excluded, simplifying the model, thus reducing the potential confounding factors of a robust theorem.
3) Increased complexity of the model (realism): In contrast to simplifying the model, efforts are made to represent one or more components of a model more realistically (e.g., Eckert & Meyer, 2024).
4) Increased parameter variation: Parameters are varied on a larger scale, allowing for certain parameter combinations that were not possible in the original model.

It is worth noting that a robustness analysis overlaps in some areas with classical sensitivity analysis but goes beyond, as it not only allows the variation of input parameters but also of the structure of the model or entire components (Grimm & Berger, 2016b)

In summary, a robustness analysis can reveal the influence of specific features of a simulation model on the results and, thereby, highlight robust theories. Additionally, it likely produces modified results that may describe the considered system differently. These altered results can further validate the model when compared to the original model and the potential properties of the system under investigation. More specifically, testing the influence of a fundamentally different modeling approach on the simulation results can assess whether results hold or change as expected in a wider range of model settings (Meyer & Schmidt, 2024). Overall, a robustness analysis tests the generalizability of the results and increases their external validity.

3 PATTERNS OF ERRORS IN PRODUCT COST INFORMATION

Notions of errors in product cost information describe prevalent ideas of how errors in product costs arise. Practitioners may be guided by these ideas to design their costing system or make cost-based decisions. Key examples are the idea that more cost pools are required to attain higher accuracy or a cross-subsidization pattern where high (low) volume product costs are biased upward (downward) (e.g., Cooper & Kaplan, 1988a). Such notions can effectively summarize critical aspects of costing system behavior without getting lost in the details. Thus, they possess high value for practice and pedagogical purposes, and prior research on costing system design has already focused on refining and testing notions (Balakrishnan et al., 2011; Hoozée & Hansen, 2018). For example, Labro and Vanhoucke (2007, 2008) investigated whether specific refinements of costing system designs increase accuracy and whether greater heterogeneity in firm environments requires higher refinement efforts to attain similar accuracy. Overall, notions often result when recurring observations (i.e., patterns) emerge to a common understanding of *how* the system under investigation "usually" works. Hence, although these notions are widespread, they can be scattered around the literature, and because the observed patterns diffuse through the literature or practice over time, their scientific foundation is often unclear (Balakrishnan et al., 2011; Labro, 2006b).

There are two reasons why this is particularly apparent for cost accounting. First, as elaborated earlier, studies in accounting and management accounting research have a low overall comparability (Shields, 2015). Reasons for this can be that proprietary datasets are used or case studies are based on individual firms (Shields, 2015). Generally, managerial accounting research focuses on company internal phenomena that are difficult to observe, which requires researchers to find innovative pathways (Eyring, Ferguson, & Koppers, 2021; Gow, 2023), decreasing the chance of reproducibility (Hail, Lang, & Leuz, 2020). This also applies to research on product costing systems.

Second, as described above, errors in cost information are empirically not measurable (Labro, 2006a) (also see Chapter 2.2.2). This further impedes the comparability of results on errors in cost information because different studies were required to employ different approximations for errors in cost information. For example, survey-based research uses proxies such as the managers' perception of accuracy of reported cost information (Hughes & Paulson Gjerde, 2003) or ABC adoption as a reaction to an increase in errors in cost information caused by an increase of drivers of errors (Brierley, 2010). Case-based studies compare a more refined costing system with a less refined costing system and argue that the more refined costing system computes more accurate cost information to infer the errors caused by the less refined costing system (e.g., Duh et al., 2009). In summary, the low comparability of results in jointness with the challenge of measuring errors in product cost information decreases the validity of current observations and corresponding results and notions (Meyer & Schmidt, 2024).

This chapter hence investigates patterns of errors in product cost information by consolidating empirical observations, theoretical predictions, and textbook-based intuitions to conceptual relationships between different aspects of costing system design, resource consumption, and errors in product cost information (see Figure 3).[21] I extract recurring observations along different systems (e.g., firms) from prior studies. In addition to the traditional approach of reviewing empirical and numerical studies, I also extract knowledge and statements from textbooks to incorporate beliefs and intuitions that are shared in cost accounting education and practice but possibly rely on few actual observations (Balakrishnan et al., 2011). The overall objective of this task is to collect the patterns in this research domain, which possibly form the notions researchers, practitioners, or lecturers have.

Table 4 overviews the patterns identified in the literature with a short description of the effect or relationship it describes, the corresponding references from empirical, analytical, and simulation studies and textbook mentions, and the overall count of references. In alignment to Figure 3, I distinguish between effects that primarily stem from the costing system design or the resource consumption and affect the system-level error. The third category, Cross-Subsidization, refers to product-level errors. Accordingly, the three categories correspond with the three analyses of this thesis (i.e., chapters 4,5,6). In Chapter 4, I focus on effects of costing system design (heuristics) on errors in reported product cost information. Chapter 5 focuses on altering resource consumption patterns to examine the robustness of a pattern from Table 4 (CSB1). Lastly, referring to the category Cross-Subsidization, I scrutinize product-level errors

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[21] I conduct an unstructured review of the literature based on a seminal-work sampling strategy (Achter et al., 2024) in which I employ the few papers that focus on errors in allocated costs as their subject of investigation as seminal-works. Due to the unobservability of errors in empirical research, these papers base on either simulation or analytical models. The papers center around a few core authors. First, Srikant Datar and Mahendra Gupta provide first structuring research of errors in product costs (Datar & Gupta, 1994; Gupta, 1993). Second Eva Labro, Ramji Balakrishnan and Vic Anand pick up these first approaches with more sophisticated simulation models and corresponding studies. (Anand et al., 2019; Balakrishnan et al., 2011; Labro, 2006a; Labro & Vanhoucke, 2007, 2008). From these papers I conduct snowballing to identify other relevant studies or textbooks. In summary, the list of notions in this thesis is not ought to be comprehensive but instead aims to provide an overview and connect it to prior studies for deeper insights (Hiebl, 2021).

in Chapter 6. I summarize and relate the findings to the patterns from Table 4 in Table 25.[22] My approach aims to employ the patterns to guide my analyses and conclude my results, as proposed by Labro (2015).

Table 4. Patterns of errors in product cost information

			Sources			
Short Name	**Name**	**Description**	**Empirical studies**	**Textbook**	**Analytical/ numerical studies**	**∑**
Costing System Design						
CSD1	Cost Pool Relationship	*A greater number of cost pools decreases the system-level error.*	Anderson, Hesford, and Young (2002); Gupta (1993); Malmi (1999); Tsifora and Chatzoglou (2016)	Balakrishnan et al. (2012a); Cooper (1988a, 1992); Cooper and Kaplan (1988a, 1991); Dopuch (1993); Emblemsvåg (2003); Labro (2006a)	Anand et al. (2017, 2019); Balakrishnan et al. (2011); Homburg et al. (2018); Labro and Vanhoucke (2007, 2008)	**19**
CSD2	Driver Sophistication	*A higher sophistication of cost drivers decreases the system-level error.*	Banker and Johnston (1993); Banker et al. (1995)	Cooper (1992); Dopuch (1993)	Babad and Balachandran (1993); Balakrishnan et al. (2011); Banker and Potter (1993); Homburg (2001); Homburg et al. (2018)	**10**
CSD3*	Willie-Sutton Rule	*A higher share of direct costs decreases the system-level error.*	Bjørnenak (1997); Brierley (2010); Noreen and Soderstrom (1997); Tsifora and Chatzoglou (2016), Rezaie et al. (2008)	Cokins (1997); Cooper (1989, 1992); Cooper and Kaplan (1988b); Franz (1993); Gunasekaran (1999); Horngren et al. (2015); Horsch (2018); Horváth and Mayer (1995); Kaplan and Cooper (1998b); Mckenzie (1999)	Banker and Potter (1993); Hundal (1997), Balakrishnan et al. (2011). Hwang et al. (1993), and Mertens (2020)	**21**

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[22] The results of the subsequent analyses provide insights to all identified patterns except the patterns CSD3 and RC5. Due to my modeling approaches I only observe cost allocation of indirect costs in a static snapshot. Hence, the results do not address a costing system's accuracy over time (RC5) or the effect of direct costs (CSD3).

Table 4 (continued).

CSD4	ABC > VBC	*ABC computes product costs more accurately than VBC.*	Duh et al. (2009); Goddard and Ooi (1998); Gunasekaran and Singh (1999); Hughes and Paulson Gjerde (2003); Sohal and Chung (1998); Turney and Stratton (1992), Tai, Wang, and Katrichis (2015), Rezaie et al. (2008)	Abernethy et al. (2001); Balakrishnan et al. (2012a); Cokins (2002); Cooper and Kaplan (1988b, 1991); Demski (2008); Dierynck and Labro (2018a); Fisher and Krumwiede (2012); Hilton (2011); Horngren et al. (2015); Kaplan (1988); Mckenzie (1999)	Christensen and Demski (1997), and Schmidt et al. (2023)	**22**
Resource Consumption						
RC1	Heterogeneity Effect	*Higher heterogeneity in resource consumption generally increases system-level errors.*	Schoute (2011), Gupta (1993), (Abernethy et al., 2001)	Cooper and Kaplan (1988b), Kaplan (1988), Hilton (2011), Horngren et al. (2015), Cooper (1989), Cooper (1992), Stuart (2013), Gunasekaran (1999)	Labro and Vanhoucke (2007), Labro and Vanhoucke (2008), Hwang et al. (1993), (Noreen, 1991), Wu et al. (2015), and Christensen and Demski (1997)	**17**
RC2	Production Quantity Effect	*A greater dissimilarity in production quantities between products increases system-level errors.*	Cooper and Kaplan (1999),Duh et al. (2009), Rezaie et al. (2008)	Cooper (1988b, 1989, 1992); Cooper and Kaplan (1988a); Gunasekaran (1999); Horngren et al. (2015); Stuart (2013)	Cooper (1988b); Shank and Govindarajan (1988), Schmidt et al. (2023)	**13**
RC3	Correlation Effect	*A lower correlation in resource consumption increases system-level errors.*	Abernethy et al. (2001); Drury and Tayles (1994, 2005)	Cooper (1988a, 1988b, 1992); Stuart (2013)	Hwang et al. (1993); Labro and Vanhoucke (2008); Noreen (1991); Wu et al. (2015); Balakrishnan et al. (2011); Noreen (1991)	**13**

Table 4 (continued).

RC4	Degree of Resource Sharing	*A lower degree of resource sharing increases system-level errors.*	Abernethy et al. (2001); Drury and Tayles (1994, 2005); Gosselin (1997)	Horsch (2018)	Balakrishnan et al. (2011); Noreen (1991); Balakrishnan et al. (2011); Homburg et al. (2018)	**9**
RC5*	Time Effect	*Resource consumption changes and increases system-level errors over time.*		Cooper (1989), Stuart (2013), Kaplan and Anderson (2003), and Labro (2019)	Anand et al. (2014) and Hoozée, Vermeire, and Bruggeman (2012)	**6**
Cross-Subsidization						
CSB1	VBC Volume-bias	*VBC systems undercost low-volume products and overcost high-volume products.*	Cooper and Kaplan (1999); Duh et al. (2009); Gietzmann (1991)	Cokins (2002); Cooper (1988b, 1989); Cooper and Kaplan (1988b, 1999); Emblemsvåg (2003); Hilton (2011); Horsch (2018)	Shank and Govindarajan (1988), and Schmidt et al. (2023)	**13**
CSB2	VBC Individuality-bias	*VBC systems undercost individualized products and overcost standard products.*		Krause and Gebhardt (2018), Schuh and Riesener (2017), (Kaplan & Cooper, 1998b)		**3**
CSB3	Dominant Undercosting	*In ABC systems more products are being under- than overcosted.*	Duh et al. (2009); Gupta (1993); Hwang and Kirby (1994)		Shank and Govindarajan (1988) Christensen and Demski (1997); Homburg et al. (2018); Hwang and Kirby (1994); Labro and Vanhoucke (2007)	**8**

Note. Patterns marked with * are not directly addressed in this thesis' numerical experiments. See the corresponding chapters for a detailed explanation.

Generally, patterns from the resource consumption category describe increasing effects on the system-level error. In contrast, patterns from costing system design describe decreasing effects, as costing system design attempts to reduce the error in reported product cost information. Since these are more controllable by firms the design of a costing system is of higher interest for researchers than less controllable factors in a firm's resource consumption. Hence, costing system design patterns have the most references in the prior literature.

Table 4 also indicates the different literature bases for different patterns. For example, the *Dominand Undercosting* pattern (CSB3) has been researched in empirical and analytical studies but has not yet been reported in textbooks[23]. In contrast, the *VBC individuality-bias* (CSB2) is heavily textbook-based with no identified empirical or analytical studies. Collectively, some notions may be more limited than others.

3.1 COSTING SYSTEM DESIGN

CSD1: Cost Pool Relationship – *A greater number of cost pools decreases the system-level error.*

The effect of increasing the number of cost pools is among the most researched relations in costing system design, as more cost pools are generally understood to decrease the system-level error directly (Horngren et al., 2015). Applying few or even only one cost pool is called "broad averaging" or "peanut-butter-costing" (Horngren et al., 2015) and is considered to result in large distortions in reported product costs, as all indirect costs are evenly distributed over the cost objects (Kaplan & Cooper, 1998b). More precisely, few cost pools increase the aggregation error in the costing system and hence, in turn, the system-level error (Labro & Vanhoucke, 2007). Prior empirical research (Anderson et al., 2002; Gupta, 1993; Malmi, 1999; Tsifora & Chatzoglou, 2016), and numerical experiments (Balakrishnan et al., 2011; Labro & Vanhoucke, 2007) generally substantiate this understanding.

CSD2: Driver Sophistication - *A higher sophistication of cost drivers decreases the system-level error.*

While the number of cost pools determines the degree of aggregation with which the costing system reflects the true consumption of overhead costs, the selected cost driver specifies the perspective on this reflection (Datar & Gupta, 1994). For example, selecting cost drivers from unit-level resource consumption will provide a different picture than cost drivers from batch-level resource consumption (Cooper & Kaplan, 1988a). The cost driver must accurately reflect the resource consumption within the corresponding cost pool. Accordingly, with more information being included in the construction of the driver (i.e., more sophisticated cost driver), the system-level error of a costing system decreases (Homburg, 2001). This is

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[23] I also include conceptual papers as textbook references, where the statement is not supported by empirical data or an analytical or simulation experiment.

corroborated by empirical (Banker & Johnston, 1993; Banker et al., 1995) and analytical studies (Balakrishnan et al., 2011; Banker & Potter, 1993; Homburg, 2001, 2005), which also conclude that (1) selecting cost drivers from different tiers of the cost hierarchy and (2) incorporating more information into each cost driver, in short, more sophisticated cost drivers, result in more accurate product costs.

CSD3: Willie-Sutton Rule - *A higher share of direct costs decreases the system-level error.*[24]
As described in Chapter 2.2 it is generally accepted that direct costs can be traced error-free to individual products, while indirect costs are allocated by a limited information costing system and thus often erroneous (Noreen, 1991). Consequently, firms with a higher share of indirect costs are prone to an increased system-level error (Mertens, 2020). Kaplan and Cooper (1998a) frame this relation as the "Willie-Sutton-Rule," which describes that costing system design refinements should focus on areas with a high share of indirect cost. The share of indirect costs is an outcome of different managerial decisions related to strategy, production and inventory, and more (Ibrahim et al., 2022). Hence, costing system designers face a given indirect cost share, making the Willie-Sutton-Rule an important pattern in costing system design and errors in cost information. Several studies noted this intuitive relationship. Empirical studies investigated the effect of a higher share of indirect costs on errors in cost information (e.g., Brierley, 2010) by observing how firms refine their costing system given different shares of indirect costs. Analytical and simulation studies model the relation directly and observe that there is a near-linear relationship between the share of indirect costs and the system-level error (e.g., Mertens, 2020).

CSD4: ABC>VBC - *ABC computes more accurate product costs than VBC.*
Conceptually, ABC systems differ from VBC systems only in the type of driver selected (i.e., activity driver compared to volume-based driver) (Labro, 2019). However, in practice, ABC systems are often more sophisticated, with a more cost pools and more information-demanding cost drivers (Brierley, 2010; Drury & Tayles, 2005). Additionally, referring to the cost hierarchy theory (Chapter 2.3), resources are consumed along different tiers. Thus, having cost drivers that explain these different tier resource consumptions is expected to result in more accurate product costs (Balakrishnan et al., 2011). This is more likely in ABC systems as activity-based cost drivers can stem from different tiers compared to volume-based cost drivers,

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[24] Since I do not distinguish between direct and indirect costs in the subsequent analyses, I do not address this pattern directly and refer to other studies that do so (e.g., Mertens, 2020).

that primarily stem from unit-level resource consumption (Kaplan & Atkinson, 1998). Thus, CSD4 states that ABC systems usually provide more accurate product costs (i.e., lower system-level error) than VBC systems. This understanding seems widely popular in all types of references. Duh et al. (2009), Tai et al. (2015), Rezaie et al. (2008) are exemplary case studies that implement an ABC system into a firm's production environment and compare the costs to the prior VBC system. Based on the differences in reported costs, these studies conclude that ABC reduces the system-level error and decreases biases in cost cross-subsidization (e.g., CSB1). Despite their usefulness, differences in reported costs must be interpreted cautiously as also more sophisticated ABC systems can produce distorted product costs (Labro & Vanhoucke, 2007).

3.2 RESOURCE CONSUMPTION

RC1: Heterogeneity Effect - *Higher heterogeneity in resource consumption generally increases system-level errors.*

Heterogeneity in resource consumption describes that resources are consumed in different patterns, which are difficult to reflect by the costing system, resulting in higher errors in cost allocation (Labro & Vanhoucke, 2008). Many studies note and observe this positive relationship between heterogeneity in general and the system-level error (see Table 4). The challenge arises as heterogeneous resource consumption is operationalized differently in these studies. For example, simulation studies apply direct measures to the modeled resource consumption (Cardinaels & Labro, 2008; Labro & Vanhoucke, 2007), surveys ask for the number of stock-keeping units (SKUs) (Schoute, 2009b), and qualitative case studies decode managers' interview responses (Abernethy et al., 2001). Additionally, textbooks also often remain vague in their understanding of heterogneity. In line with the definition of resource consumption and the possible patterns that are relevant for cost allocation (in Chapter 2.3), three recurring specifications of heterogeneity independently affect the system-level error - production quantities, correlation in resource consumption, and the degree of resource sharing (patterns RC2, RC3, and RC4), which I elaborate on below.

RC2: Production Quantity Effect - *A greater dissimilarity in production quantities between products increases system-level errors.*

Differences in production quantities for different products in a firm's product portfolio are usually easy to measure (Anand et al., 2019). Hence, firms use these numbers as proxies for differences in resource consumption and to design their costing systems (Cooper & Kaplan, 1988b). Based on this, studies observed that greater disparities between different products' production volumes result in more difficult to account for resource consumption patterns, causing an increased system-level error (Duh et al., 2009; Shank & Govindarajan, 1988). Although this effect is particularly apparent for VBC systems (Horngren et al., 2015) it can also apply to ABC systems (Schmidt et al., 2023).

RC3: Correlation Effect - *A lower correlation in resource consumption increases system-level errors.*

The second recurring aspect of heterogeneity is the correlation between the consumption of different resources(Balakrishnan et al., 2011). This directly relates to the concept of the cost hierarchy described in Chapter 2.3. More specifically, the correlation within resource consumption describes whether the consumption patterns of different resources are positively, negatively, or not related to each other and thus can or cannot be reflected by a shared cost driver of these resources (Meyer & Schmidt, 2024). According to Noreen (1991) a positive (ideal linear) relation between a cost driver and all its represented resources is a pivotal requirement for accurately allocating costs. Consequently, if different resource consumption patterns correlate negatively, different cost drivers with similar distinct consumption patterns are required to compute accurate product costs. This has also been observed in several empirical studies where firms with different consumption patterns employ corresponding cost drives.(Abernethy et al., 2001; Drury & Tayles, 1994, 2005; Foster & Gupta, 1990).

RC4: Degree of Resource Sharing - *A lower degree of resource sharing increases system-level errors.*

The degree of resource sharing can be seen as a posterior effect of the correlation in resource consumption (Balakrishnan et al., 2011). More resource sharing, as in process-shop production, means that different products have more commonly consumed resources (e.g., all products produced on the same production line). This results in a more homogeneous resource consumption overall and, thus, in higher correlations (RC3). In contrast, there are fewer common resources in a production environment with less resource sharing, such as job-shop production. This increases the demand for more cost drivers to allocate costs accurately, or, in other words, increases system-level errors when the costing system is not adjusted. On the other hand, it increases the traceability of costs, as consumption might be easier to distinguish with lower degrees of sharing (Kerremans et al., 1991). This refers to the Willie-Sutton-Rule (CSD3). Overall, a lower degree of resource sharing increases the system-level error *if* the affected resources and costs are not directly traced to individual products but allocated using the costing system.

RC5: Time Effect - *Resource consumption changes and increases system-level errors over time.*[25]

The Time Effect pattern (RC5) relates to the understanding that the resource consumption of a firm changes over time (e.g., due to product-mix decisions) (Anand et al., 2017) and hence increases the system-level error if the costing system design is not adapted accordingly (Cooper, 1989). Although this effect is, according to Labro (2019), lacking empirical and simulation research, it is commonly referenced in textbook-based literature (Stuart, 2013) and seems widely acknowledged. There are only two studies that aim to investigate this effect in more detail - Anand et al. (2014) and Hoozée et al. (2012). Both studies focus on the refinement or update of a costing system after a change in resource consumption and stress the importance of adapting the costing system design regarding the system-level error. Although most of this research is focused on how to update the costing system, there are a few listed indicators that signal when to update, or in other words, when the system-level error is high. Table 5 lists such indicators with corresponding references and explanatory comments. Arguably, these indicators partially overlap with the relations in Table 4, but have the objective of providing more precise and tangible proxies for when the system-level error is high and an update of the costing system may be required.

Table 5. Indicators that signal higher errors in product cost information

	Indicator/Signal	**Reference**	**Comment**
1	"*functional managers want to drop seemingly profitable lines*"	(Cooper, 1989; Cooper & Kaplan, 1999)	Managers don't believe the costs of the costing system anymore
2	"*profit margins are hard to explain*"	(Cooper, 1989)	
3	"*hard-to-make products show big profits*"	(Cooper, 1989)	If complex products are not priced at premium and still show lucrative profit margins, the costing system likely undercosts these products.
4	"*departments have their own cost systems*"	(Cooper, 1989)	Similar to (1).

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[25] The subsequent modeling experiments do not address this pattern directly as they do not observe a costing system's behavior concerning errors in reported product cost over time.

Table 5 (continued).

5	“*the accounting department spends a lot of time on special projects*”	(Cooper, 1989)	When cost information accuracy play an important role for a special decision and the costing system does not provide this information, so that accountants put in a lot of effort to measure information.
6	“*you have a high-margin niche all to yourself*”	(Cooper, 1989)	Given no barriers of market entry, there should be competition. If not, it may be that the costing system reports distorted costs.
7	“*competitor’s prices are unrealistically low*”	(Cooper, 1989)	When similar firms provide similar products but at lower prices, the averaging of your costing system may distort your costs.
8	*“customers don’t mind price increases”*	(Cooper, 1989)	
9	*“the results of bids are hard to explain”*	(Cooper, 1989)	When the pricing of the firm is off.
10	*“vendor bids are hard to explain”*	(Cooper, 1989)	If vendor bids are much lower/higher than producing the product by themselves, may hint to a faulty costing system.
11	*“reported costs change because of new financial accounting regulatios"*	(Cooper, 1989)	Costing systems that are aimed to meet financial reporting requirements “don’t do a good jo of meeting other” objectives.
12	*Unspecified cost drivers*	(Balakrishnan et al., 2011)	Similar to CSD2.
13	*Diversity in the size of cost pools*	(Labro & Vanhoucke, 2008)	The greater the cost-wise size difference between different resource cost pools, the greater the payoff from costing system refinements.
14	*Diversity in proportional resource consumption at each cost pool*	(Labro & Vanhoucke, 2008)	The greater the difference in proportional resource usage at each cost pool, the greater the payoff from costing system refinements.
15	*Increase in competition in product markets*	(Horngren et al., 2015)	
16	*Changes to the production technology used*	(Cooper, 1989; Kerremans et al., 1991; Stuart, 2013)	For instance, increased automation that shifts costs to other tiers in the cost hierarchy.

3.3 CROSS-SUBSIDIZATION

CSB1: VBC Volume bias - *VBC systems undercost low-volume products and overcost high-volume products.*

The system-level error likely does not evenly spread over all products in a firm's product portfolio, but instead, some products have higher product-level errors than others, some are overcosted (positive product-level error), and some are undercosted (negative product-level error) (Hilton, 2011). Since the total costs are usually known to a firm (Balakrishnan et al., 2012a), products will cross-subsidize in their costs, where some products carry the costs of others. The costing system determines which products are over- or undercosted and have a lower or higher product-level error in their costs (Schmidt et al., 2023). Different costing systems introduce different biases into the cross-subsidization as these costing systems are distorted toward the cost driver they measure (Labro, 2006a). More specifically, if the cost driver overstates (understates) the true consumption of a product, that product is overcosted (undercosted). VBC systems employ cost drivers based on the production volumes of a product; thus, if a product's production volume overstates (understates) the true resource consumption of indirect costs, these products will be overcosted (undercosted). This is more likely for high-volume products because their absolute production volumes are higher than low-volume products, resulting in the VBC Volume-bias. This bias in VBC systems is widely acknowledged in the cost accounting literature and has been observed in several empirical case studies and numerical experiments (see Table 4, CSB1). Additionally, it is even considered among the main reasons for the development of ABC (Horngren et al., 2015) and, thus an important outcome of costing systems to understand errors in cost information (Schmidt et al., 2023).[26]

CSB2: VBC Individuality bias - *VBC systems undercost complex products and overcost simple products.*

Products that attract more customers are likewise produced in larger quantities to satisfy the greater demand (Kekre & Srinivasan, 1990). In that regard, economic theory suggests that these products address more common and standard customer needs than products that satisfy niche or exotic needs and are produced in lower quantities (Lancaster, 1990). Accordingly, high-volume products are usually simpler, more standardized products that contain only the basic functional requirements, while low-volume products contain several functional requirements and are thus considered more individualized toward specific customer needs (Elmaraghy et al., 2013; Suh, 2001; Ulrich, 1995). This individualization results in greater consumption of non-volume related activities (e.g., product design and research and development) (Anderson, 1995; Fisher & Ittner, 1999; Myrodia et al., 2021), which in turn is underestimated if corresponding

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[26] The mechanism behind the volume bias in VBC systems is analyzed in Schmidt et al. (2023) and chapter 5 of this thesis.

costs are allocated based on the low production volumes for these products. In other words, due to the association between a product's individualization and production volumes, VBC systems undercost individualized products and overcost standard products (Elmaraghy et al., 2013; Schuh & Riesener, 2017).[27] Interestingly, although this pattern is closely related to the VBC volume-bias pattern (CSB1), most empirical or numerical studies neglect this perspective in their analysis (e.g., Gietzmann, 1991; Shank & Govindarajan, 1988). Thus, the pattern is widely spread conceptually but has not yet been specifically tested.

CSB3: Dominant Undercosting – *In ABC systems more products are being under- than overcosted.*

ABC advocates long reasoned the superiority of ABC systems due to its ability not systematically to distort product costs (Cokins, 2002). However, prior case studies (e.g., Duh et al., 2009; Gupta, 1993) report that ABC tends to undercost the majority of products in a portfolio. This has been more closely examined in numerical studies from Christensen and Demski (1997) and Labro and Vanhoucke (2007). Both studies find that few products are largely overcosted, with most products being slightly undercosted.

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[27] Although this pattern overlaps with the VBC volume-bias (CSB1), I consider it as a standalone effect as its underlying mechanism is different (Schmidt et al., 2023)

4 INVESTIGATION OF DESIGN HEURISTICS ROBUSTNESS BASED ON A MODEL REPLICATION OF BALAKRISHNAN ET AL. (2011)[28]

4.1 INTRODUCTION

When designing a costing system, firms use design heuristics to reduce efforts while achieving sufficiently accurate costs to efficiently trade off costs of measuring costs with costs of errors (see Figure 2). For example, based on the *Willie-Sutton-Rule* (CSD3 in Table 4) costing system designers are guided to focus on resources with high costs when forming cost pools and selecting cost drivers (Kaplan & Cooper, 1998b). As a result, the resource consumption of these costs is more accurately approximated, which can result in a more accurate allocation to products. From this understanding, several patterns (listed in Table 4) of the effect of costing system design on errors in reported cost information have emerged, signaling its importance in cost accounting.

Balakrishnan et al. (2011) understand the importance of evaluating the effectiveness of costing system design heuristics and employ numerical experiments to provide essential insights. Their study is the first to compare these design heuristics that primarily stem from intuition, simplified textbook reasoning (Kaplan & Cooper, 1998b), or single observations of costing systems (Hwang et al., 1993). Their simulation-based approach provides a rigorous computational testbed for a comparative analysis of these heuristics. Hence, their study is interesting from a theoretical perspective and essential for practitioners when designing a costing system. It has a strong orientation toward practice as the tested design rules are easily implementable rather than theoretical optimizations (Kaplan & Cooper, 1998b). Overall, this makes BHL an essential contribution to this field of research.[29]

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[28] This chapter is based on the working paper Meyer, M., & Schmidt, M. (2024). Robust design heuristics for product costing systems: a replication and extension using an ABC cost hierarchy. Journal of Business Economics, *Forthcoming*. I adapt and extend the results and include analyses that are not in the underlying paper or in its appendix and align the discussion of this chapter to the overall objective of this thesis. This applies to the chapters starting on pages 45 to 81, including figures and tables.

[29] The practical importance of their study is further highlighted by receiving the 2014 Greatest Potential Impact on Practice Award by the Management Accounting Section of the American Accounting Association. Additionally, the study satisfies three out of four criteria from Salterio (2014) to be considered a central study for replication. The listed reasons are (1) publication in a FT50 journal, (2) challenging prior beliefs (i.e., textbook guidance on

Given the importance of the study and its practical implications, it is vital to scrutinize their validity because, as for any study, there are potential threats to its results' internal and external validity and associated recommendations (Libby et al., 2002) (see Chapter 2.5 and 2.6).

In the context of external validity, cost accounting research and ABC literature often discusses the existence of an ABC cost hierarchy (Anderson & Sedatole, 2013), distinguishing between different levels of non-unit-level costs, such as costs related to product design (i.e., product-sustaining-level) (Labro, 2004) or batch set-up costs (i.e., batch-level) (Banker et al., 2021b) (as described in chapter 2.3). This results in a resource consumption pattern where single resources are consumed either more proportionally (i.e., with higher positive correlation) or more disproportionally (i.e., with stronger negative correlation) along the different tiers of an ABC cost hierarchy (Noreen, 1991). Thus, compared to the modeling in BHL, the consumption of different resources is less random, which can be utilized by costing system design heuristics to increase the accuracy of reported costs but may also be detrimental to the accuracy in costing systems that do not utilize this. Remarkably, this resource consumption pattern has not been implemented in the modeling of ABC systems, although an ABC cost hierarchy is considered the raison d'etre for implementing an ABC system (Cooper & Kaplan, 1991).[30] Hence, the external validity of design heuristics – given an ABC cost hierarchy – still needs to be scrutinized because resource consumption may follow different patterns, which require other design heuristics to achieve sufficient accuracy.

For these reasons, this chapter aims to test the internal and external validity of BHL’s results concerning the design heuristics of costing systems. I proceed in two steps. First, I start by closely replicating the model and reimplementing it in a different software environment based on the conceptual description provided in BHL. This helps to rule out implementation specificities or programming errors, increases the internal validity upon successful replication, as intended by model replication (Wilensky & Rand, 2007) (also see Chapter 2.5), and sets a comparable base. I reconduct the numerical experiments concerning the design heuristics of the original paper and assess their replicability in the new software environment, thereby scrutinizing their internal validity. Second, I implement an ABC cost hierarchy in the resource

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costing system design), and (3) has substantial implications for practitioners. The Financial Times Research Rank (FT50) lists the 50 most impactful business and economics-related journals based on the rankings provided by surveyed business schools. BHL is published in *Management Science*, which is listed in the ranking.

[30] As a notable exception Schmidt et al. (2023) and the thereupon based chapter 5 of this thesis implement an ABC cost hierarchy in the replicated framework from Anand et al. (2019). However, in their analysis both works focus on volume-based cost drivers and do not analyze the effect on design heuristics in ABC or in general.

consumption generation of the replicated simulation model that extends the original approach from BHL and is based on theoretical predictions and empirical observations from the literature, as described in Chapter 2.3. More precisely, I insert a four-tier ABC cost hierarchy into the resource consumption of the modeled production environment by setting the respective share of costs and resources for each tier and controlling the correlations in resource consumption between the different tiers of the ABC cost hierarchy. This results in a more heterogeneous and structured true resource consumption that the costing system must reflect to compute accurate product cost information. By rerunning the simulation experiment in this modified production environment, I conduct a robustness analysis in the form that Grimm and Berger (2016a) suggested and as described in Chapter 2.6 to test the external validity of the results concerning costing system design heuristics. The external validity increases when the results hold (Libby et al., 2002).

The results from the close replication show that the conducted experiment can reproduce most of the selected results concerning costing system design heuristics with high alignment to the original paper. I found only one exception where reproduced effects are less profound than in the original paper. Still, I conclude a successful replication of selected results from Balakrishnan et al. (2011). From the perspective of internal validity, the results and recommendations are mainly valid.

Regarding the conducted robustness analysis of costing system design heuristics, I observe that the main conclusions from BHL still hold. However, I also observe several effects of the ABC cost hierarchy on the performance of different costing system design heuristics. More specifically, the results show that when an ABC cost hierarchy is present in the true resource consumption, simple costing systems are more likely to outperform subsequent, more refined costing systems compared to resource consumption without an ABC cost hierarchy. I relate this finding to two potential effects caused by the ABC cost hierarchy. First, I argue that true resource consumption follows more structured patterns when the ABC cost hierarchy is present and has higher information content. Simple costing system designs that exploit the additional information content can benefit from it regarding their accuracy. Second, I understand that the effect of errors offsetting each other increases. These offsetting effects in cost allocation describe that cost measurement in different cost drivers of the costing system deviate upward or downward in equal magnitudes and thus cancel each other out so that reasonable accuracy is achieved for the final product costs (Datar & Gupta, 1994). These deviations may stem from all error types within costing systems (i.e., measurement, specification, and aggregation errors) and are caused by the costing system design (Datar & Gupta, 1994). Accordingly, improving the costing system in one aspect (e.g., by increasing the number of cost drivers) may result in reduced accuracy because offsetting effects are reduced (e.g., because the additional cost drivers are inaccurate) (Labro & Vanhoucke, 2007). Because of this effect, less information-demanding costing system designs and respective design rules can become more accurate overall. As a result of these effects, the pay-off from incremental costing system design refinements becomes less predictable, favoring very simple costing system designs. Collectively, when considering the external validity of the results of the simulation experiments, one needs to consider the existence of an ABC cost hierarchy.

This chapter adds to the overall contribution of this thesis in three ways. First, it replicates and extends the simulation model from Balakrishnan et al. (2011) and thus test the validity of respective results. For this, I implement the empirically derived ABC cost hierarchy from Chapter 2.3 to extend the simulation model. This adds to the complete understanding of the effects of costing system design and resource consumption in errors in cost information.

Second, as Balakrishnan et al. (2011) investigate the efficacy of costing system design heuristics regarding errors in cost information, the analysis of this chapter examines these design heuristics and corresponding patterns of CSD1 (Cost Pool Relationship) and CSD2 (Driver Sophistication) from Table 4.

Third, by analyzing the efficacy of different design heuristics, this chapter also takes a closer look at the trade-off of costs of costing systems (see Figure 2). This trade-off describes that firms must balance the costs of implementing and maintaining information-demanding costing systems with the costs of errors from distorted cost information (Cooper, 1989). Although this is conceptually intuitive, there is little numerical or empirical evidence on whether more refined information-demanding costing systems result in lower errors to justify this trade-off. The results of this chapter show that there can be profound exceptions to this rule and indicates that incremental refinements toward medium information-demanding costing systems may even result in higher errors in cost information. In summary, this chapter focuses on costing system design recommendations to provide an updated understanding of corresponding patterns in Table 4 (CSD-pattern).

The analysis in this chapter is structured as follows. Chapter 4.2 discusses prior considerations for the replication and extension approach. Moreover, I derive theoretical expectations on how the implemented ABC cost hierarchy may affect results reported by BHL. Chapter 4.3 describes the simulation model and design of the numerical experiment. Chapter 4.4 presents the results of the close replication and contrasts selected figures from BHL with their reproduced counterparts. Chapter 4.5 presents the modeling approach for the ABC cost hierarchy based on the literature review in Chapter 2.3, and Chapter 4.6 investigates its effect on costing system design heuristics by conducting a second simulation experiment. Finally, Chapter 4.7 concludes this analysis by summarizing the results and discussing the findings.

4.2 PRIOR CONSIDERATIONS

This investigation aims to test the validity of costing system design heuristics based on the results from Balakrishnan et al. (2011). To test the validity, I pursue a two-step approach. First, I aim to replicate selected results from the original paper closely by following best practices of model replication, as described in Chapter 2.5 (e.g., Burman et al., 2010; Schmidt et al., 2023; Wilensky & Rand, 2007).

In the second step, I extend the original model by changing critical assumptions to investigate whether results remain valid toward these assumptions that follow different theories or updated empirical evidence to conduct a robustness analysis (Grimm & Berger, 2016a). More specifically, I implement a four-tier ABC cost hierarchy described in Chapter 2.3 to extend the modeled resource consumption. I select the resource consumption pattern to be a suitable model assumption for this robustness analysis as it is the main element (apart from the design of the costing system) that drives the accuracy of reported product costs, as shown by prior simulation studies (Homburg et al., 2018; Labro & Vanhoucke, 2008). Moreover, an ABC cost hierarchy is considered the raison d'etre for implementing an ABC system (Cooper & Kaplan, 1991). Additionally, there is a lengthy and still pending discussion about the relevance and presence of an ABC cost hierarchy in firms' resource consumption (Anderson & Sedatole, 2013; Banker et al., 2021b). Although there are several supporting studies for this updated theory (Banker & Johnston, 2006), the number, sizes, and correlations of different tiers of resources and activities in a cost hierarchy are still unclear (Anderson & Sedatole, 2013). BHL model a two-tier cost hierarchy where they separate volume-level from batch-level costs while defining a relatively even distribution of these two tiers[31]. In contrast, the ABC cost hierarchy distinguishes between four different tiers –unit-level, batch-level, product-sustaining, and facility-sustaining-level (Cooper & Kaplan, 1991). The objective is to investigate whether BHL's results for costing system design heuristics still hold under an ABC cost hierarchy with four tiers and empirically derived ratios for the resource and cost sizes and correlations of resource consumption (see Chapter 2.3). Figure 5 conceptually compares the two cost hierarchies of the respective modeling approaches.

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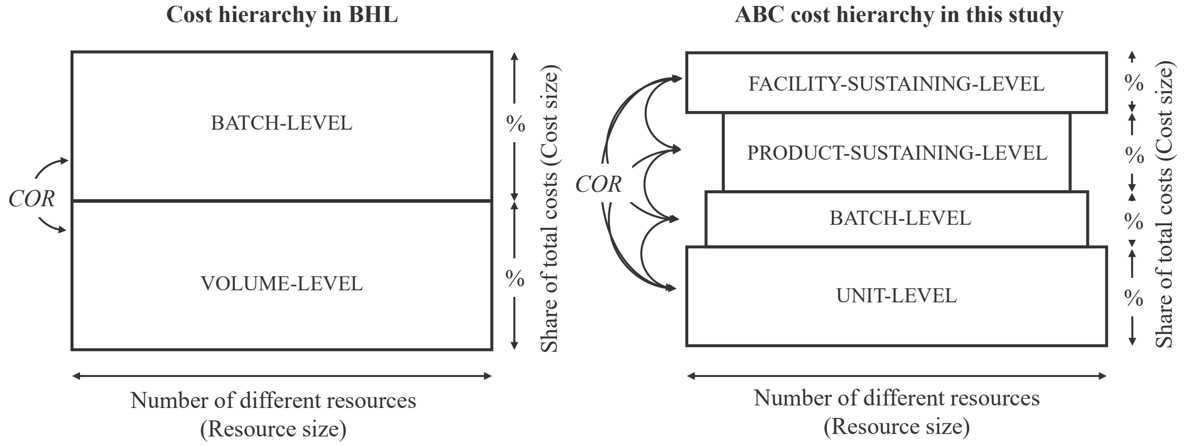
[31] They model approximately 50% of resources to be batch-level that account for 20 – 50% of total costs.

Figure 5. Conceptual structures of different cost hierarchies



Note. *COR* refers to the correlation of resource consumption patterns between the cost hierarchy's different tiers. The number of different resources (Resource size) specifies how many different resources are consumed or activities performed in a particular tier. The share of total costs (Cost size) specifies the fraction of all costs evoked by the resources/activities within a tier. Please note that many different resources do not necessarily imply a high share of total costs.

To evaluate the internal and external validity of results, I focus on the key results from BHL and assess whether they are affected by either step of the validity test (i.e., close replication and robustness analysis). I use this approach to guide the analysis because simulation experiments provide a vast output space (e.g., many variables and sub-experiments are possible) and because their results are often too complex to report (Labro, 2015). Therefore, I follow the general suggestion to use patterns to focus the reported results (Grimm et al., 2005; Heine et al., 2005; Schmidt et al., 2023). BHL provide a summary of key results in their paper's appendix, which can be employed as the focal point of the replication analyses and for which I formulate theoretical expectations on how these results may be affected by an ABC cost hierarchy (see Table 6).

Table 6. Overview of key findings to assess the validity of results concerning heuristics

Result/Finding in BHL	**Description (quoted from BHL, p. 540-541)**	**Expectations given ABC cost hierarchy**
Forming Cost Pools		
Result P1; Figure 1	*When the distribution of resource costs is moderately skewed (top 20% of costs account for less than 40% of total costs), correlation-based methods dominate size-based methods. When the distribution of resource costs is highly skewed (top 20% of costs account for greater than 75% of total costs), size-based methods dominate correlation-based methods.*	I expect this result to generally hold as it is not directly associated with the resource consumption pattern.
Result P2; Figure 2	*A blended method that groups resources into tiers and uses a size-based rule within each tier results in an error comparable to that obtained with more information-intensive methods.*	The grouping into tiers along the ABC cost hierarchy will become even more critical.
Result P4; Figure 1	*For all methods assigning resources to cost pools, it is generally preferable to group the costs of low-cost resources into one pool rather than distribute them over the other pools.*	With an ABC cost hierarchy, resource consumption is more heterogeneous, worsening the performance of grouping the costs of low-cost resources into one cost pool.
Result P5; Figure 1	*A moderate number of cost pools (10–20) seem enough, regardless of the method used to group resources into cost pools. For both size-based and correlation-based methods, the gain from adding more pools is concave in the number of pools formed.*	In a more heterogeneous setting where an ABC cost hierarchy is present, more cost pools may be necessary to achieve similar accuracy compared to a less heterogeneous setting.
Selecting Cost Drivers		
Result D1	*In every environment and method for grouping resources into cost pools, an indexed driver is preferred to the "big-pool" method of using the consumption pattern for the largest resource.*	I expect this result to become even more profound in the ABC cost hierarchy setting because the resource consumption becomes less correlated. Therefore, more information-demanding cost drivers should capture the different consumption patterns more accurately. Additionally, cost drivers should be taken from every tier of the ABC cost hierarchy to approximate true resource consumption accurately.

Table 6 (continued).

Result D2; Figure 3	*Indexed drivers (using four or five resources) might do better than the more information-intensive average driver with a moderate (8–12) number of cost pools.*	I expect that information-demanding cost drivers (i.e., average) outperform simpler cost drivers because the resource consumption becomes more heterogeneous with the ABC cost hierarchy. Hence, more information is required to achieve similar accuracy.

The costing system design choices of firms generally consist of three aspects – the number of cost pools, the method used to group resources into cost pools, and the method used to select cost drivers. First, increasing the number of cost pools leads to a more disaggregated reflection of true resource consumption (Datar & Gupta, 1994), which, on average, results in more accurate product costs (Result P5). This is also a recurring pattern of errors in cost information (see CSD1 in Table 4). At the same time, this increases the information demand because more cost pools must be formed, and the cost drivers of each cost pool must be measured (Homburg, 2001). Accordingly, firms group resources into a limited number of cost pools to reduce the number of different costs (e.g., activities or departments) to be measured while maintaining sufficient accuracy (Labro & Vanhoucke, 2007). Resources can be grouped by relying on the size of resources – size-based rules – or the correlations in the pattern of resource consumption – correlation-based rules. Size-based rules are easier to implement because cost-wise large resources are known to the firm (e.g., from financial accounting) (Balakrishnan et al., 2012a). Correlation-based rules are more information-demanding than size-based rules because they require a firm to know the resource consumption of different resources and how these relate to each other (Balakrishnan et al., 2011). Given that the latter uses more information about resource consumption, it is assumed to outperform the former, except when few resources account for a significant fraction of total costs (Result P1). Then, measuring the consumption of these few expensive resources is worthwhile to obtain accurate costs.

Next, when selecting cost drivers, firms aim to select drivers that approximate the true resource consumption within the respective cost pool. Accordingly, increasing the informational input for a cost driver increases its ability to reflect the details of the true resource consumption (Results D1 and D2). For instance, this can be achieved by incorporating the information about the resource consumption of two or more resources into a cost driver compared to measuring the consumption pattern of only one resource as the cost driver.

Generally, as described above, the costing system design aims to capture true resource consumption as accurately as possible while balancing the implementation and measurement efforts of the costing system. Since BHL model a two-tier cost hierarchy they find that distinguishing between resources of the two different tiers is beneficial for costing system accuracy (Result P2). In that way, resource consumption within a cost pool becomes more homogeneous. As indicated by BHL, this is the core idea of ABC (Cooper & Kaplan, 1988b). This can also be supported by grouping low-cost resources into one cost pool rather than distributing them among all cost pools (Result P4).

On average, a more information-demanding costing system should report more accurate product costs because more information about the true resource consumption is captured instead of approximated. The results in Table 6 describe this relation but also point out exceptions to this rule, where simpler, less information-demanding costing system design rules outperform their information-intensive counterparts. These exceptions benefit costing system designers, as they inform them where less information-demanding and cheaper costing systems provide accurate product costs. By implementing an ABC cost hierarchy, it can be expected that some of these exceptions may hold and increase in significance while others diminish. I argue that the ABC cost hierarchy increases the heterogeneity of the true resource consumption and makes it more structured. As described in Chapter 2.3 the effect of heterogeneity in resource consumption[32] is considered one of the main drivers of errors in reported costs and, hence, costing system design (Christensen & Demski, 1997; Gupta, 1993; Hwang et al., 1993). Labro and Vanhoucke (2008) define this heterogeneity as a multifaceted construct that is reflected by "*(1) differences in how resources are shared among activities and products across the whole of the costing system, (2) differences in proportional resource usage by activities and products at a particular cost pool, and (3) differences in the dollar size of different cost pools"*(Labro & Vanhoucke, 2008, p. 1716). As I alter the true resource consumption of a firm's product portfolio, I argue that implementing an ABC cost hierarchy addresses aspect *(1)* of the definition from Labro and Vanhoucke (2008). As this paper aims to test the validity of different costing system designs and heuristics, I focus on a treatment that addresses aspect *(1)* – the heterogeneity in true resource consumption – and leaves the costing system design unchanged. Textbooks and prior studies define this type of heterogeneity as the degree of differing resource consumption by different products (Hilton, 2011). Hence, with more significant differences in the consumption

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[32] See also Chapter 3.2 for further descriptions of heterogeneity in resource consumption and their assumed effects on errors in product costs.

of resources, more information is required to approximate true consumption for all products and their product costs.

Per this understanding and modeling, an ABC cost hierarchy[33] directly affects the differences in consumption by introducing resources consumed in structurally different patterns than other resources (e.g., product-sustaining resources vs. unit-level resources) (Banker et al., 2021b). However, by doing so, I argue that it also introduces more structure to the resource consumption of a firm. It separates different resources into four tiers and assumes that intra-tier resource consumption is strongly correlated while inter-tier resource consumption is unrelated or negatively correlated (Schmidt et al., 2023). This characteristic of an ABC cost hierarchy and corresponding resource consumption evokes two likely contradicting effects that both address the traditional intuition that more information-demanding costing systems generate more accurate product costs. First, I expect the more structured resource consumption and its higher information content to be exploited by design heuristics, which can benefit their accuracy-related performance. Second, the increased heterogeneity in resource consumption may increase the probability of errors offsetting each other in very simple costing systems (Datar & Gupta, 1994). Although different, both effects may create situations where very simple costing systems could outperform subsequent, more information-demanding costing systems. These effects are thus highly relevant for practitioners and address the external validity of results concerning costing system design heuristics from BHL.

4.3 MODEL DESCRIPTION AND REPLICATION APPROACH

4.3.1 MODEL DESCRIPTION

The model of Balakrishnan et al. (2011) involves of two main elements – the *benchmark system* and the *costing system*. The *benchmark system* describes a firm comprising resource costs, produced products, and resource consumption that links the spent resource costs to individual products. The *costing system* represents an aggregated benchmark system aiming to allocate resource costs to individual products accurately. To achieve this, the costing system forms cost

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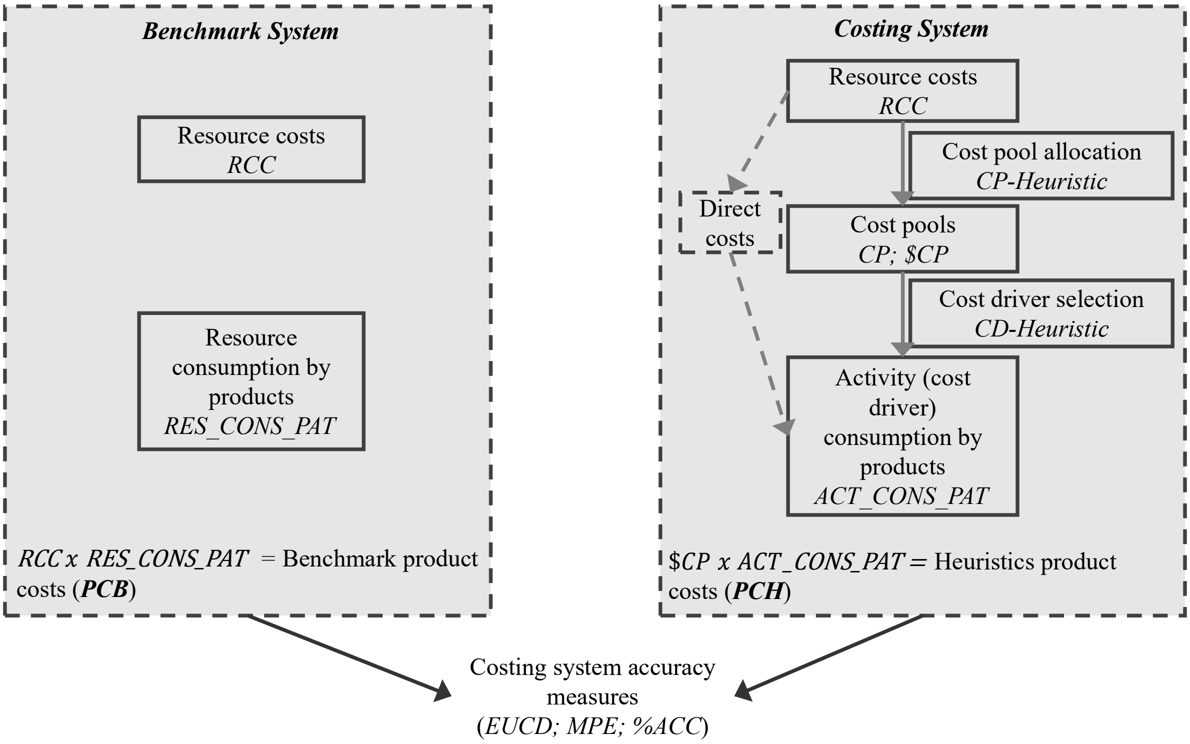
[33] Note that the modeled cost hierarchy is termed an ABC cost hierarchy because it distinguishes between the four tiers introduced by the ABC literature – unit-level, batch-level, product-sustaining-level, and facility-sustaining-level costs (Cooper & Kaplan, 1991). In a broader definition, a cost hierarchy can also follow different structures and have other tiers of resource consumption (Banker & Johnston, 2006). The ABC differentiation appears to be the most prominent one. Other studies term this ABC cost hierarchy only as cost hierarchy (Anderson & Sedatole, 2013; Balakrishnan et al., 2012a; Banker et al., 2021b) or as the ABC hierarchy (Labro, 2004, 2019).

pools and selects cost drivers based on limited information retrieved from the benchmark system. The costing system design is based on heuristics that resemble rules of thumb, textbook guidance, or intuition when designing a costing system (Balakrishnan et al., 2011). Figure 6 provides a conceptual overview of the model's main elements and functionality. A detailed description of the simulation model can be found in the original paper (Balakrishnan et al., 2011).[34]

Figure 6. Conceptual Model



Note. *RCC* = Resource costs; *RES_CONS_PAT* = Resource consumption pattern matrix; *PCB* = Benchmark product costs; *CP-Heuristic* = Heuristic used for allocating resource costs to cost pools; *CP* = (Activity) cost pools; *$CP* = Dollar value for each *CP*; *CD-Heuristic* = Heuristic used for selecting cost drivers; ACT_CONS_PAT = Activity consumption pattern matrix; *PCH* = Heuristics' (reported) product costs; *EUCD* = Euclidean Distance; *MPE* = Mean percentage error; *%ACC* = Share of accurately costed products.

The model starts by generating *RCC*, the vector containing each resource's costs. First, the user determines the dissimilarity of resource costs among all resources in *RCC* by setting a value to the input variable *RC_VAR*, which defines the standard deviation of the normal distribution from which the random values in *RCC* are drawn. The greater the chosen value of *RC_VAR*, the greater the differences between all resources' costs. Next, the model draws a random value

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[34] A further detailed description of the simulation was provided by the original paper's authors for this replication. Their support is highly appreciated.

from a uniform distribution of 0.2 and 0.5 boundaries. The value determines the share of total costs assigned to batch-level resources (e.g., machine set-ups) (*PER_BATCH*). Hence, between 20% and 50% of total costs are consumed by batch-level resources. In total, the model generates 50 resources.

As the second element of the *benchmark system*, the model generates the resource consumption matrix *RES_CONS_PAT* that determines how individual products consume resources. Specific patterns within this matrix reflect different resource consumption patterns linked to different cost structures or production environments (e.g., flow-shop, work-shop) to generalize the findings over different industries (Balakrishnan et al., 2011). To generate the *RES_CONS_PAT* matrix, the model uses the input parameters *DENS* and *COR*. *DENS* defines the density of the matrix. High density resembles a high degree of resource sharing, meaning resources are more commonly shared among products, which may be the case for a mass production line. *COR* defines the correlation of batch-level resource consumption with unit-level resource consumption. The model distinguishes between two areas in the *RES_CONS_PAT* matrix, which correspond to the volume-level and batch-level resources in the *RCC* vector. For this, half of the modeled resources (i.e., 25) are unit- and batch-level resources, respectively. The greater the value for *COR*, the more significant is the correlation of resource consumption between the batch-level tier and the volume-level tier of the *RES_CONS_PAT*. Accordingly, if the batch-level resources' consumption patterns correlate negatively (positively) with the unit-level consumption patterns, the true resource consumption would (not) distinguish between the two tiers. Hence, with negative values for *COR*, the modeled cost hierarchy consists of two tiers (see Figure 5). A consumption pattern for a resource i (i.e., a column in the resource consumption matrix *RES_CONS_PAT*) RC_i is generated as:

$$RC_i = InputCor * BASE + \sqrt{1 - InputCor^2} * RandomValue$$

InputCor resembles the input variable *COR* for batch-level resources. *BASE* and *RandomValue* are values drawn from a normal distribution for each product. *BASE* resembles a resource consumed by every product independent from *DENS*. In the original model, the value for *InputCor* for unit-level resource consumption is set to U[0.2;0.8] independently from *COR* and for all settings. Next, the model sets approximately the *DENS* share of entries in *RES_CONS_PAT* to zero and normalizes the remaining non-zero values to reflect the percentage of resource consumption. The model multiplies the resource cost vector *RCC* with the *RES_CONS_PAT* matrix to obtain the true benchmark product costs *PCB*. The sum of all product costs in *PCB* equals the sum of spent resource costs in *RCC*.

The model follows two tasks when generating the *costing system*: building cost pools and selecting cost drivers. For this, the input variable *CP* defines the costing system's number of (activity) cost pools.[35] Next, the model employs six different heuristics with increasing degrees of information demand to build cost pools, as listed below.

1) *Random*: Resources from *RCC* are randomly distributed along a defined number of cost pools *CP*. Each activity cost pool should contain approximately the same number of resources. This design heuristic requires no particular information because it is purely random.
2) *Size-Random*: Each activity cost pool is seeded with one of the *CP* largest resources from *RCC*. The remaining resources are randomly distributed over all activity cost pools, so each pool holds approximately the same number of resources. Here, the costing system designer requires information about the cost-wise largest resources.
3) *Size-Misc*: The largest *CP*-1 resources from *RCC* are seeded into *CP*-1 activity cost pools. The remaining resources are allocated to a miscellaneous cost pool. Here, the costing system designer again requires information about the cost-wise largest resources.
4) *Correlation-Random*: Each activity cost pool is seeded with one randomly drawn resource from *RCC*. The remaining resources are allocated via their correlation to the seed-resource, so each activity cost pool contains approximately the same number of resources. This design heuristic requires information about the correlation between seeded and remaining resources. Measuring and relating a resource’s consumption pattern to other resources’ consumption patterns is information-demanding (Balakrishnan et al., 2011).
5) *Correlation-Size*: Each activity cost pool is seeded with one of the *CP* largest resources from *RCC*. The remaining resources are allocated via their correlation to the seed-resource, so each activity cost pool contains approximately the same number of resources. Like the above heuristic, this design heuristic also requires information-intensive correlation knowledge and further information about the cost-wise largest resources.
6) *Blended*: The model distinguishes between unit-level and batch-level resources. Each group of resources is assigned to one-half of *CP* cost pools using the *size-random* heuristic. Although this design heuristic employs the relatively simple size-random method, it requires prior knowledge about the respective tier of every resource (i.e.,

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[35] Note that Balakrishnan et al. (2011) employ the terms activity pool and activity cost pool synonymously.

unit-level and batch-level). This differentiation may be easy for the costing system designer in some settings. However, research is still inconclusive about the relationship between different resources' consumption patterns (Foster & Gupta, 1990) and argues that resource consumption is easily misinterpreted when related to production volume (Cooper & Kaplan, 1991; Schmidt et al., 2023). Collectively, it may be information demanding to distinguish between different tiers of resource consumption.

The model employs the following heuristics to select cost drivers for each activity cost pool, with increasing information demand, as the resource consumption patterns of more resources must be measured when more resources are included in the cost driver.

1) *BIGPOOL:* Only the cost-wise largest resource in a cost pool is set as the cost driver.
2) *Indexed*: This method averages a prior-defined number of the cost-wise largest resources of an activity cost pool as the driver. For instance, Num = 2 (in short, *Num2*) means that the average resource consumption of the two cost-wise largest resources in a cost pool is set as the cost driver of that activity cost pool. With a larger value for Num, more resources are included in the cost driver.
3) *Average*: The average resource consumption of all resources in an activity cost pool is set as the driver of that cost pool.

With the selected cost drivers, the model generates the activity consumption matrix *ACT_CONS_PAT*, which can be seen as an aggregated *RES_CONS_PAT* that does not have complete information about every resource's consumption. Additionally, the model assumes a measurement error in the cost drivers (Cardinaels & Labro, 2008) between ±10% and ±50% of the true resource consumption. Finally, by multiplying *ACT_CONS_PAT* with the dollar value for each *CP ($CP)*, the model calculates the heuristics product costs *PCH*, representing the product costs reported by the costing system. The sum of all products' costs *PCH* (or *PCB*) equals the sum of *RCC*.

To compare true and reported product costs (*PCB* and *PCH*) and evaluate the effectiveness of the different heuristics, Balakrishnan et al. (2011) compute three different accuracy measures.[36]

1) *EUCD*: Euclidean Distance between *PCH* and *PCB*, calculated as $\sqrt{\sum_{i=1}^{CO}(PCB_i - PCH_i)^2}$
2) *%ACC*: The materiality measure measures the percentage share of products that are materially undercosted or overcosted (Labro & Vanhoucke, 2007). Kaplan and

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[36] Also see Table 1 for additional accuracy and error measures and further explanations.

Atkinson (1998) set this threshold at a 5% deviation from true costs. *%ACC* is calculated as $(\frac{1}{CO})\sum_{i=1}^{CO}\begin{cases}1\ if\ 0.95\ PCB_i < PCH_i < 1.05\ PCB_i; \\ \quad 0\ otherwise;\end{cases}$ (Labro & Vanhoucke, 2007).

3) *MPE*: The mean percentage error between *PCH* and *PCB,* calculated as $\left(\frac{1}{CO}\right)\sum_{i=1}^{CO}\frac{|PCB_i - PCH_i|}{PCB_i}$

4.3.2 Design of Numerical Experiments

To replicate the selected results of the original paper, I will conduct the same experiments with the replicated model. More precisely, the focus is on the design heuristics for costing systems and the corresponding results (see Table 6). Hence, I replicate Figure 1 Panel A and B, Figure 2, and Figure 3 Panel A and B of BHL. Additionally, I replicate Table 1 of BHL as it provides a general overview of the model's functionality and benchmark system and thus serves as a baseline test of whether the replication was successful (Results in Table 8).

Table 7 below illustrates the design of experiments for this replication approach following the recommendations in Lorscheid et al. (2012). I precisely reconduct the numerical experiment from BHL with 960 randomly generated benchmark systems and 300 unique costing systems to obtain 14,400 design points (i.e., input parameter combinations) and 288,000 unique observations. The parameter values for the input variables are chosen accordingly and varied systematically. These variables are the leading independent variables for the numerical replication experiment, while the output variables are the primary dependent variables. Additionally, I control for further variables that affect the model’s behavior but are not part of the primary analysis.

Table 7. Design of experiments for replication following Lorscheid et al. (2012)

Input variables		**Control variables**		**Output variables**
Benchmark System		*PER_BATCH* Share of costs that are assigned to batch-level resources	U[0.2;0.5]	*EUCD* Euclidean distance between true and reported product costs
RC_VAR Disparity of resource costs	0.25,0.5,0.75	*Runs* Number of runs for each input variable combination	20	*%ACC* Share of product costs that are within the materiality threshold (5%)

Table 7 (continued).

DENS Degree of resource sharing	-0.75,0,0.75,1.5	*ME*[37] Measurement error in the cost driver	U[0.1;0.5]	*MPE* Mean percentage error between true and reported product costs
COR Correlation between batch-level and unit-level resource consumption	0.33,0,-0.33,-0.66	*NUMB_PRO* Number of products in the product portfolio	50	
		NUMB_RES Number of resources in RCC	50	
Costing System				
CP Number of activity cost pools in the costing system	1,2,4,6,8,10			
CP-Heuristic Employed cost pool allocation heuristic	*Random, Size-Random, Size-Misc, Correlation-Random, Correlation-Size, Blended*			
CD-Heuristic Employed cost driver selection heuristic	*BIGPOOL, Num=2, Num=4, Num=5, Average*			

Note. Design points = 3*4*4*10*6*5= 14,400; Observations = 14,400*20 = 288,000

To evaluate replication success, I compare the descriptive statistics of the replicated Table 1 (Table 8 in this thesis) and the replicated figures (Figure 7, Figure 8, and Figure 9 in this thesis). For this, I primarily employ relational and distributional equivalence as the replication success criteria by comparing the curve progressions in the respective figures and the means of each observation point. I would require further quantitative results to apply more sophisticated approaches for distributional equivalence (Fachada et al., 2017). However, I relate to the replication approach in Schmidt et al. (2023) and argue that a qualitative assessment of replication results is sufficient concerning the design heuristics for costing systems because

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[37] Similar to the original paper, the effect of *ME* appeared to be trivial and was therefore left out of the replication analysis.

these provide general guidance instead of quantifications. Moreover, this follows the recommendations of Labro (2015) to focus on qualitative results in simulation research. Overall, achieving relational and distributional equivalence in the replicated table and figures would indicate the high internal validity of the tested results.

4.4 CLOSE REPLICATION RESULTS

The close replication of the original model from BHL indicates alignment with the original paper's results, as I generally reproduce the model's output. First, I recompute Table 1 from the original paper and compare the different metrics to the reproduced computations (see Table 8). The replicated model computes near-similar values for all metrics in Table 8. By doing so, it can be shown that (1) the provided explanations to calculate these metrics are sufficient for recalculation, and (2) the replicated model's behavior is generally similar to the original model's. However, as noted above, numerical equivalence is nearly impossible in stochastic models (Belding, 2000).

Consequently, I find minor deviations between the two models in nearly all metrics in Table 8. These minor deviations do not necessarily affect the overall model's behavior and results but can add up to create larger effects. In particular, deviations in the correlations between the resource consumption of the largest and all other resources and between the resource consumption of the largest and batch resources (Table 8 Panel A) arise. The replicated model produces weaker positive and stronger negative correlations than the original model. The model description for generating the resource consumption matrix is detailed and unambiguous. Therefore, I assume a potential explanation for these differences is using different software and random number generators. I contacted the authors of BHL, who suggested the same explanation for these differences. Nevertheless, relational and distributional equivalence for the results reported in Table 8 can be concluded.

Table 8. Descriptive Statistics

Panel A: Benchmark cost systems - Characteristics systematically varied

			Average values				
Variation resource costs (using parameter RC_VAR)	Units	Study	Global average	Low dispersion (RC_VAR = 0.25)	Med dispersion (RC_VAR = 0.50)	High dispersion (RC_VAR = 0.75)	
			N=960	N=320	N=320	N=320	
Percentage of cost in largest pool/percentage of cost in smallest pool	Ratio	BHL	6.78	3.2	5.75	11.39	
		REP	6.88	3.29	5.93	11.42	
Percentage of cost in top 10 resources	%	BHL	34	30	34	39	
		REP	34	30	34	37	

Density of consumption matrix (using parameter DENS)			Global average	Little sharing of resources (DENS = -0.75)	Medium sharing of resources (DENS = 0)	High sharing of resources (DENS = 0.75)	Very high sharing of resources (DENS = 1.50)
		Study	N=960	N=240	N=240	N=240	N=240
Percentage of zero entries in the consumption matrix	%	BHL	36.04	70.95	46.11	20.87	6.22
		REP	38.32	75.51	48.73	22.20	6.83
Average number of products consuming a resource	Number (max. = 50)	BHL	31.97	14.52	26.94	39.56	46.88
		REP	30.84	12.25	25.63	38.90	46.58
Average range in consumption of a resource across products (given positive use)	%	BHL	11.43	23.22	11.08	6.61	4.79
		REP	11.09	22.06	10.94	6.62	4.75

Importance of resources devoted to batch activities (using parameter COR)			Global average	Similar consumption patterns (COR = 0.33)	Intermediate consumption patterns (COR = 0.0)	Intermediate consumption patterns (COR = -0.33)	Dissimilar consumption patterns (COR = -0.66)
		Study	N=960	N=240	N=240	N=240	N=240
Correlation between largest pool and all resources	Number	BHL	0.264	0.376	0.298	0.232	0.149
		REP	0.102	0.202	0.124	0.069	0.013
Correlation between largest pool and batch resources	Number	BHL	-0.029	0.3	0	-0.061	-0.125
		REP	-0.045	0.138	0.000	-0.113	-0.207

Table 8 (continued).

Panel B: Benchmark cost systems - Characteristics not systematically varied

Characteristic	Unit	Study	Average	Median	Interquartile range
Percentage of resources in pools devoted to batch activities	Percent	BHL	35.07	34.87	14.14
		REP	35.09	35.01	15.51
Correlation between largest pool and volume resources	Number	BHL	29.36	29.6	15.6
		REP	29.07	29.45	18.19

Panel C: Error metrics - Univariate statistics (N = 17,280)

	Study	Mean	Min	Quartile 1	Quartile 2	Quartile 3	Max
EUCD	BHL	28448	2514	16237	24882	36919	124155
	REP	33840	2280	17928	29288	45120	284562
%ACC	BHL	25.844	0	14	22	34	100
	REP	23.826	0	12	18	30	100
MPE	BHL	16.8	1.47	9.66	14.92	21.82	62.59
	REP	19.93	1.23	10.56	17.44	26.76	187.11

Panel D: Correlation among error metrics (N = 17,280)

	EUCD		%ACC		MPE	
	BHL	REP	BHL	REP	BHL	REP
EUCD	1	1	-0.745	-0.718	0.955	0.981
%ACC			1	1	-0.769	-0.730
MPE					1	1

Note. N specifies the number of observations in the corresponding sub-sample. Columns or rows marked with REP contain values computed with the replicated model.

4.4.1 Forming Cost Pools

Next, I compare Figure 1 Panel A from BHL and observe a high similarity between the original model's results and the reproduced results (Figure 7 Panel A). More precisely, the performance order of the different cost pool allocation heuristics remains, while minor differences in absolute accuracy (*EUCD*) arise for some heuristics. Additionally, the result that more cost pools increase accuracy generally holds (Result P5). Thus, the pattern CSD1 of Table 4, which states this positive relation between the number of cost pools and the accuracy of a costing system, holds in the replicated simulation model.

For Panel B of Figure 1, the replicated model does not reproduce the results for all the applied cost pool allocation heuristics. While the results for the *correlation-based* method with an *Average* cost driver generally hold, the *EUCD* for the other methods substantially differs from the original model (Figure 7 Panel B). More precisely, the *random* and *size-random* methods are more accurate than the original model, while the method *size-misc* is notably less accurate than in the original model. To interpret this finding, one should note that for this result, I had to conduct an additional experiment to achieve the required share of costs in the top 20% of resources because the experiment described in BHL only results in resource costs that are more evenly distributed.[38] Upon contacting the original paper's authors, I learned that they increased the input parameter *RC_VAR* even further compared to the experiment in Table 7 to achieve the required skewness in resource costs. I followed their guidance and set *RC_VAR* to 0.75,1,1.25,1.5,1.75,2 while fixing CP to 10 and leaving all other parameters as in the baseline experiment (Table 7). Upon further clarification with the original paper's authors, they also assumed that the differences between the original and the replicated models likely stem from the deviations in the correlations of the resource consumption matrix (Table 8). This assumption is further substantiated by untabulated results, which show that increasing the number of cost pools to more than 10 increases the alignment of the two figures. Accordingly, the resource consumption matrix in the replicated model seems more heterogeneous than in the original model, wherefore a greater disaggregation is required to achieve a similar accuracy. To summarize, I only partially replicate Panel B of Figure 7 and conclude that when resource costs are disparate, the dominance of size-based rules over correlation-based rules is less robust (Result P1).

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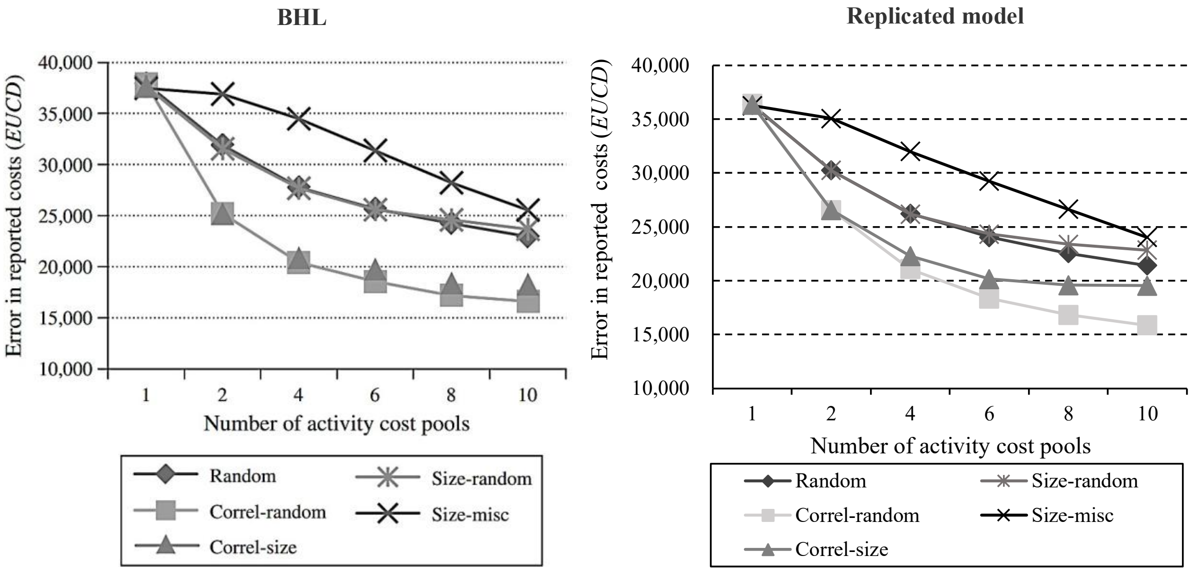
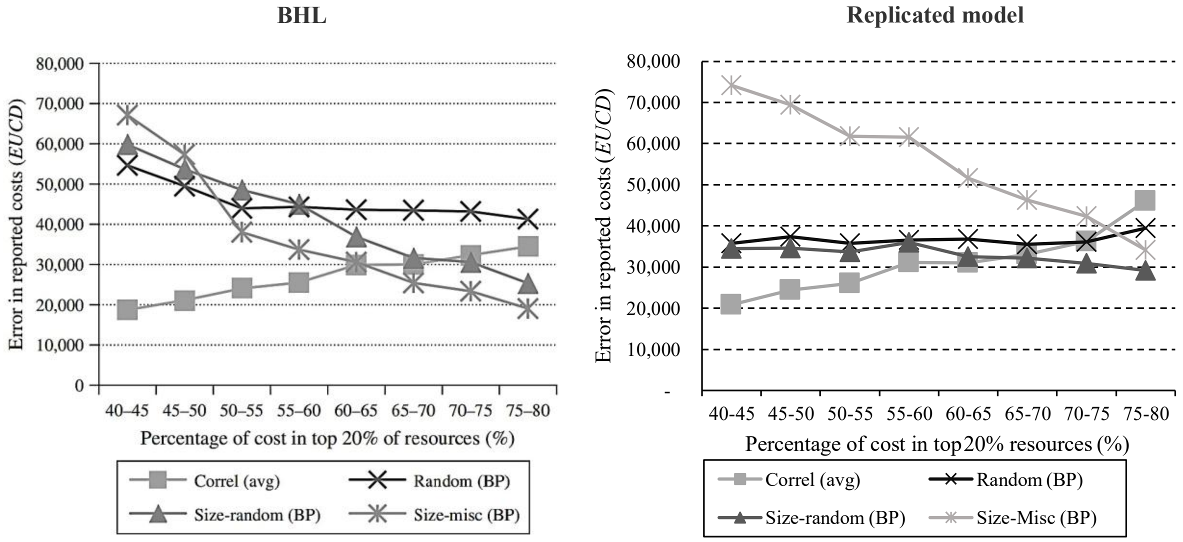
[38] See Panel A in Table 8. The top 20% of resources (i.e., the largest 10 resources) have an average share of 34% of total costs.

Figure 7. Replication of Figure 1 of BHL

Panel A: Comparison of assignment methods: baseline experiment

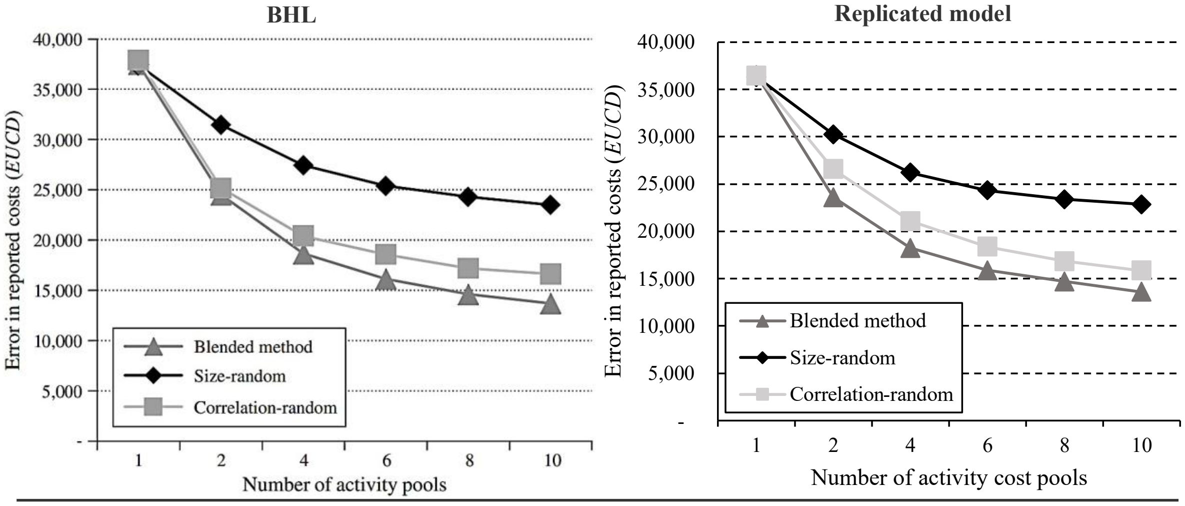


Panel B: Comparison of assignment methods with skewed resource costs



The results in Figure 2 in BHL (see Figure 8) can be reproduced almost identically. I also find that the *blended* method performs best for grouping resource costs into cost pools (Result P4).

Figure 8. Replication of Figure 2 of BHL

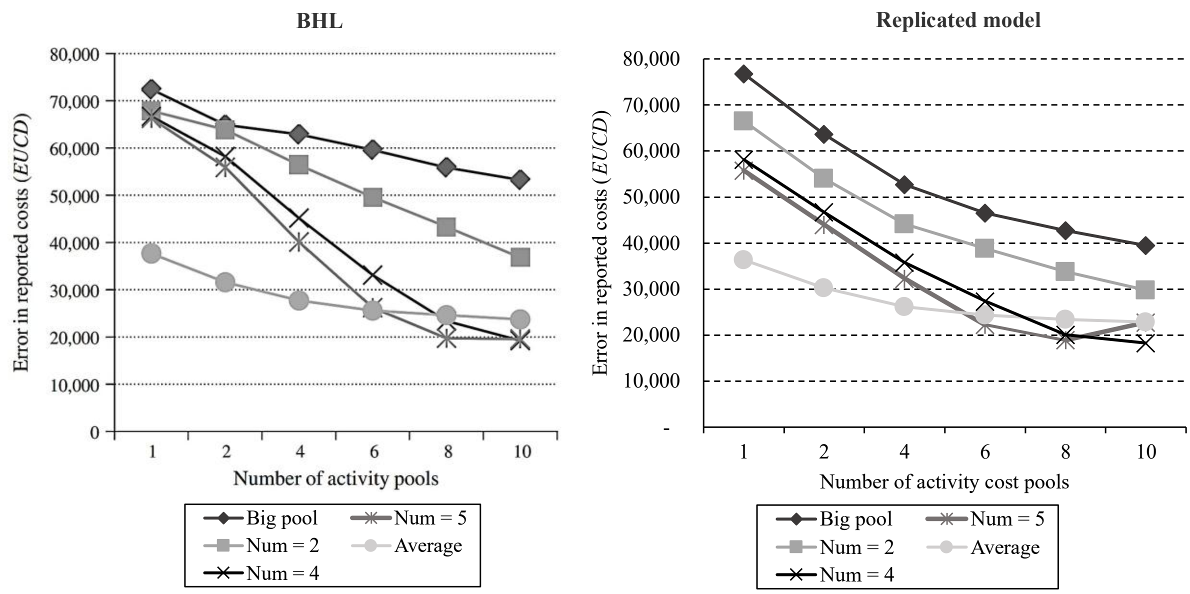


4.4.2 SELECTING COST DRIVERS

Figure 9 shows the replication results for Figure 3, Panel A, and Panel B in BHL. The figures from the replicated model differ slightly from their counterparts in the original model. More precisely, the replicated model produces more linear curve progressions for the different cost driver heuristics than in the original paper. In turn, there are more profound differences in accuracy between the heuristics when the costing system only employs one cost pool. Although these results differ from the original paper, they can be rationalized. A cost driver that considers the resource consumption of several resources should report more accurate product costs than a cost driver that only measures one resource's consumption pattern (e.g., *BIGPOOL* vs. *Num2* vs *Average*). Potential explanations for this result discrepancy may be the different correlations in resource consumption patterns or more minor deviations in the precise algorithms of the heuristics (either the underlying *CP-Heuristic* or the respective *CD-Heuristic*). Although the replication results differ slightly from the original paper's results, I argue that the overall qualitative statements remain similar and are, hence, replicated (Results D1 and D2).

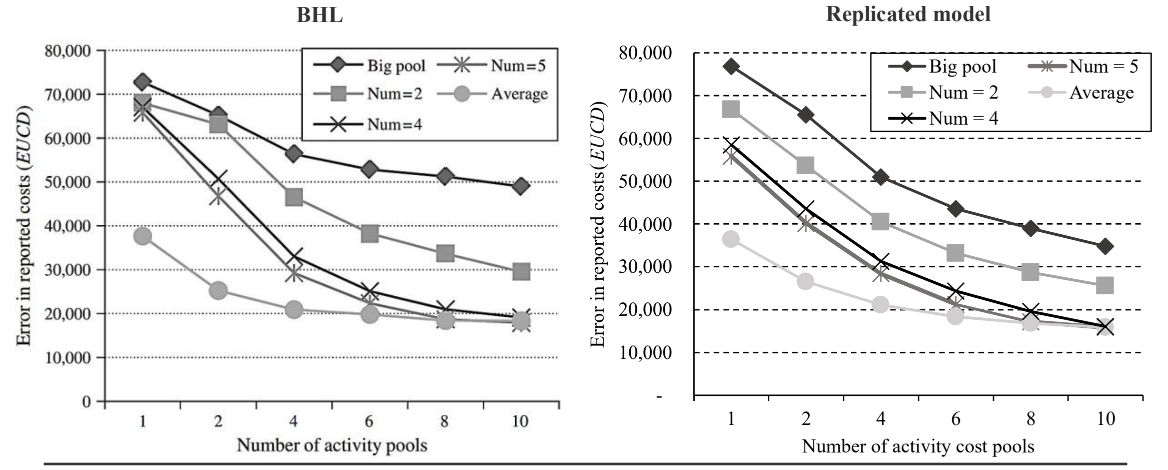
Figure 9. Replication of Figure 3 of BHL

Panel A: Use of size-random method to assign resources to activity pools


BHL

Replicated model

Panel B: Use of correlation-random method to assign resources to activity pools


BHL

Replicated model

Overall, the results show minor deviations between the original and the replicated models' results. However, the replicated model generally reproduces the most results concerning costing system design heuristics. The only major exception is Panel B of Figure 7, where the results do not align for all heuristics, affecting the corresponding result in Table 6 (Result P1). Since this result requires an undescribed additional experiment, it can be argued that the other results are independent of this. I assess the replication success by achieving relational equivalence, as Axtell et al. (1996) describe. I also test for distributional equivalence by comparing the quantifications in Table 8 and the observation points in the figures. In summary, I evaluate the replication as successful and the results as internally valid.

4.5 IMPLEMENTATION OF AN ABC COST HIERARCHY

The original model in BHL distinguishes between two tiers of resources (i.e., volume and batch resources) whose resource consumption is either positively or negatively correlated (see Figure 5). In contrast, as described in Chapter 2.3, the ABC literature advocates a separation of resource consumption patterns into four tiers: unit-level, batch-level, product-sustaining-level, and facility-sustaining-level tiers (Anderson & Sedatole, 2013). This chapter aims to implement a four-tier ABC cost hierarchy to test the external validity of the results concerning costing system design heuristics toward this change.

I model the ABC cost hierarchy based on the described theoretical considerations and empirical observations using the ratios and correlations in Table 2 and Table 3 of this thesis. I solely adjust the resource consumption pattern in the benchmark system by modeling the ABC cost hierarchy into the resource consumption matrix *RES_CONS_PAT* and resource cost vector *RCC*. The costing system design heuristics (i.e., cost pool allocation and cost driver selection heuristics) remain unchanged as in the original model to compare their performance.[39]

The ABC cost hierarchy modeling follows the original model's mechanics and only adjusts specific input settings. Like the original model, the resource cost vector *RCC* is split into different tiers. BHL determine that approximately half of all resources are volume- and batch-level, respectively, whereby 20-50% of total costs are distributed among batch-level resources (see Figure 5). In contrast, for the ABC cost hierarchy, I separate *RCC* into four tiers (see Figure 5), where each tier has the approximate share of resources and costs as indicated by the average of the different observations from prior studies (Table 3 in Chapter 2.3). To achieve desired correlations and (dis)proportionality between the different tiers' resource consumption, I employ a similar approach as in the original model. More specifically, I continue to model unit-level resource consumption exactly as volume-level resource consumption in the original model. I reuse the variable *COR* to set the correlation of batch-level resource consumption to unit-level resource consumption but draw it from U[0;-0.66]. Thus, the correlation between batch-level resources and unit-level resources is negative, while batch-level resources are positively correlated with each other (Mertens, 2020; Misra, 1975). For product-level resource consumption, I set *COR* as for unit-level resource consumption to U[0.2;0.8] but multiply the drawn value for each product-level resource with a random factor U[0;05]. Thus, product-level resources have a lower within and between-tier correlation but can correlate positively with

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[39] An exception is made for the *blended* method, which is slightly adjusted to account for the four tiers in the ABC cost hierarchy compared to the two tiers in the original model's cost hierarchy. An overview comparison between the models is illustrated in Table 27 in the appendix of this paper.

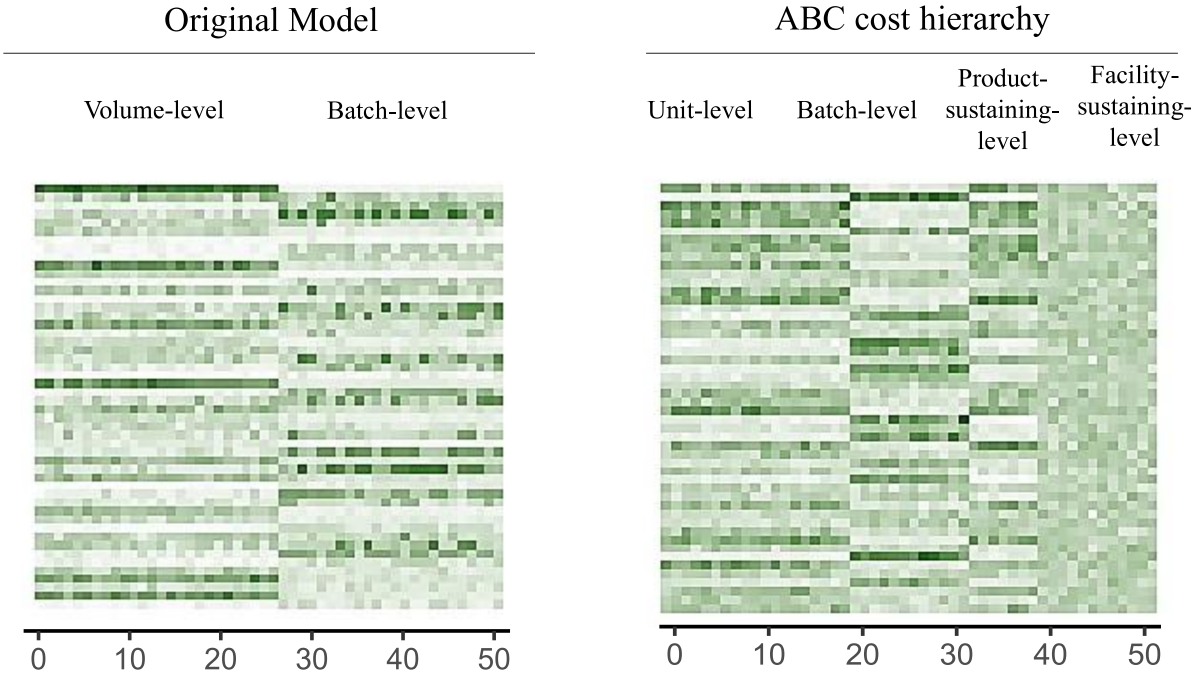
unit-level resource consumption. This approximately equals a value of 0.33 for *COR* on average, corresponding to the modeling in Schmidt et al. (2023). Finally, facility-level resource consumption is randomly generated as it is fully decoupled from unit-level resource consumption and corresponding production activities. Lastly, I implement the degree of resource sharing by employing the variable *DENS* as in the original model. Table 9 lists the achieved correlations and standard deviations (in brackets) for the closely replicated model and the model with an implemented ABC cost hierarchy. Additionally, Figure 10 compares exemplary cost hierarchies from both modeling approaches, the original model and the ABC cost hierarchy extension.

Table 9. Modeled correlations between tiers of the ABC cost hierarchy

		ORIGINAL MODEL			
Tier	Input COR	Unit	Batch	Product	Facility
Unit		1			
Batch	0.33;0;-0.33;-0.66	-0.16 [0.60]	1		
Product	-	-	-	1	
Facility	-	-	-	-	1
		ABC COST HIERARCHY EXTENSION			
Unit		1			
Batch	-0.33;-0.66	-0.73 [0.15]	1		
Product	0.33	0.48 [0.14]	-0.43 [0.13]	1	
Facility	0	0.00 [0.14]	0.00 [0.14]	0.00 [0.14]	1
Modeled Cost Share [%]		45	19	17	19
Modeled Resource Share [%]		35	46	8.3	9.7

Note. The values resemble the averaged calculated output correlations between the resource consumption patterns of the two tiers in the respective row and column. The values in brackets resemble the corresponding standard deviation. Note that values are calculated based on the generated *RES_CONS_PAT*, whose computation process is described in Chapter 4.3.1.

Figure 10. Exemplary comparison of modeled cost hierarchies



Note. Dark-shaded cells resemble higher resource consumption, and light-shaded cells indicate lower relative resource consumption of the corresponding resource (column) by the corresponding product (row). Consequently, the emerging color patterns imply differently correlated resource consumptions across the different tiers.
The original model's respective relative resource sizes are volume-level: 50%; batch-level: 50%. The relative cost sizes are volume-level: 50%-80%; batch-level 20%-50%.
The ABC cost hierarchy model's respective relative resource sizes are, on average, the unit-level: 35%; batch-level: 46%; product-sustaining-level: 8.3%; facility-sustaining-level: 9.7%. The respective relative cost sizes are the unit-level: 45%; the batch-level: 19%; product-sustaining-level: 17%; facility-sustaining-level: 19%. The shown cost hierarchies are exemplary. Cost and resource sizes vary due to random number generation.

I understand the ABC cost hierarchy and resulting resource consumption as a more segregated and heterogeneous true resource consumption pattern. As described in Table 6, this change can be expected to affect the costing system design heuristics and associated results.

4.6 ROBUSTNESS ANALYSIS RESULTS

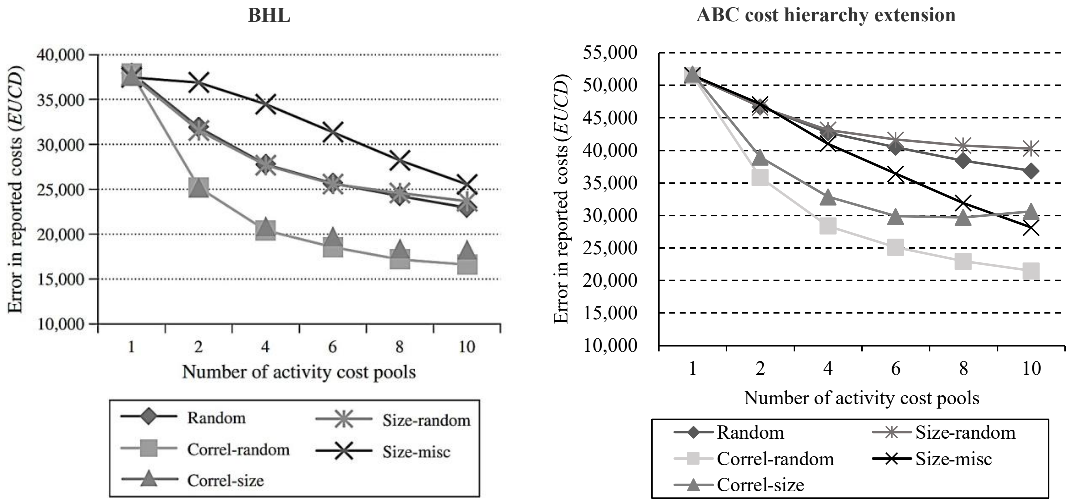
4.6.1 FORMING COST POOLS

To analyze the validity of the results concerning costing system design heuristics toward an ABC cost hierarchy, I recompute the replicated figures of the close replication. Starting with Figure 1 in BHL, Figure 11 Panel A shows that introducing an ABC cost hierarchy into the resource consumption pattern affects the overall performance of all cost pool allocation heuristics as the *EUCD* increases on average (note the different y-axes). Hence, to achieve similar levels of accuracy, more cost pools are required (Result P5). Additionally, the *size-misc* heuristic performs better with more cost pools than in the original model, resulting in a changed order of the heuristics. Accordingly, grouping low-cost resources into a miscellaneous cost pool appears even more worthwhile than in the original model. The recommendation in Result P4 is reinforced when an ABC cost hierarchy is present.

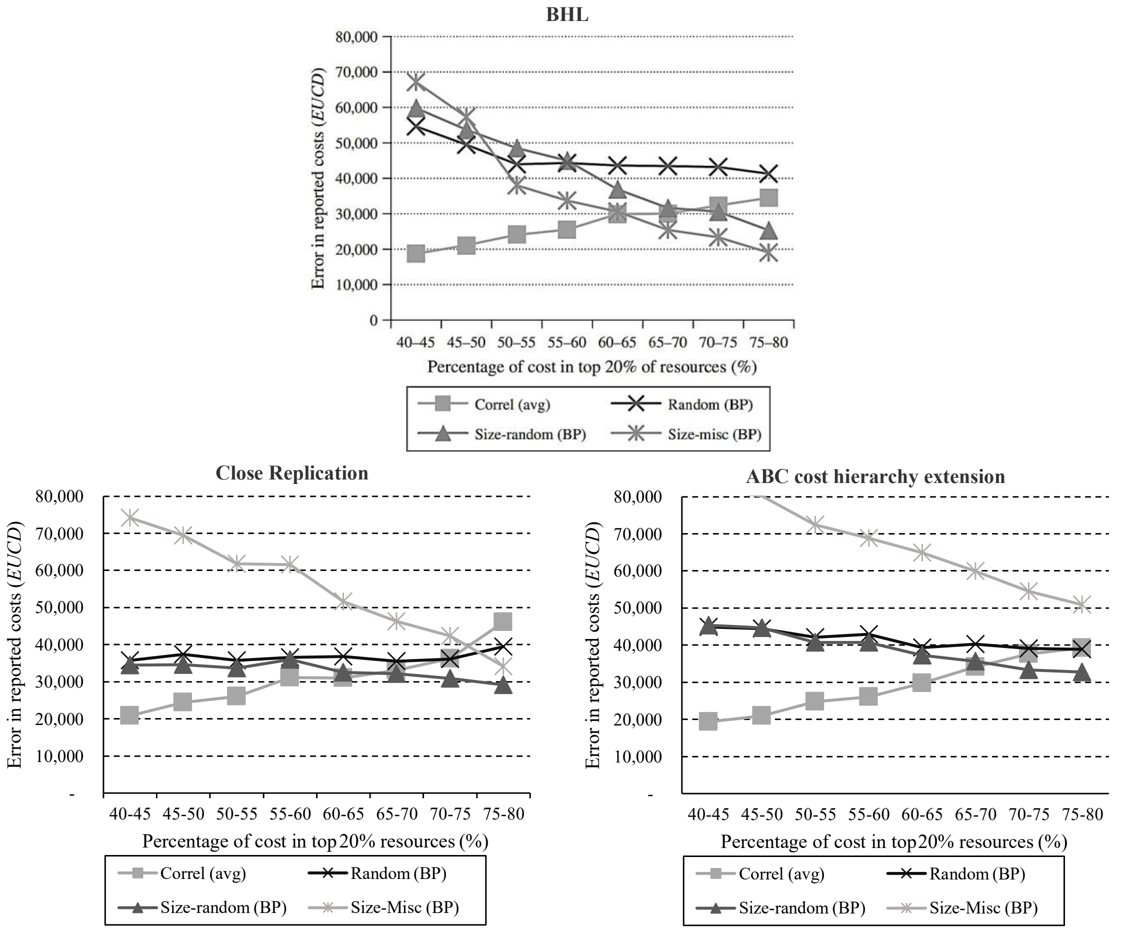
For Panel B of Figure 1 in BHL, Figure 11 Panel B illustrates that the performance of the *size-misc* heuristic with a *BIGPOOL* cost driver further decreases compared to the other heuristics. However, it is the only heuristic that increases accuracy with increasing resource cost disparity. Still, in contrast to the original model, the heuristic size-random with a *BIGPOOL* cost driver outperforms *size-misc*. Arguably, as I could not reproduce the results precisely as in BHL, this result may also be driven by the differences in the close replication itself (also depicted in Figure 11 Panel B). However, in comparison to the close replication, Figure 11 Panel B illustrates an even more substantial outperformance of *size-random* over *size-misc* when the ABC cost hierarchy is present. Hence, in this case, distributing low-cost resources over cost pools results in more accurate product costs than pooling them into one miscellaneous cost pool. This outcome challenges the recommendation of Result P4 (building a miscellaneous pool is preferable over distributing low-cost resources). Finally, the accuracy of reported product costs when using the heuristic *correlation-random* with an *Average* cost driver decreases with increasing disparity in resource costs. This is in line with the original model from BHL.

Figure 11. Robustness analysis of Figure 1 of BHL

Panel A: Comparison of assignment methods: baseline experiment



Panel B: Comparison of assignment methods with skewed resource costs



I test the validity of the results concerning the *blended* method (Figure 2 in BHL) by reconducting the same experiment under the presence of an ABC cost hierarchy while also providing an *updated blended* method that employs the changes in the resource consumption pattern of the ABC cost hierarchy. The original *blended* method distinguishes between volume-level and batch-level resources when grouping resources into cost pools. This differentiation does not apply under the ABC cost hierarchy, as it separates resources into four tiers instead of two. To adjust the *blended* method to this new structure, I calculated which two tiers' resource consumption patterns are most like each other (i.e., the correlation between the two tiers' resource consumption). These two tiers' resources are grouped into one group, and the other two tiers' resources into the other group. Then, I apply the *blended* method as in the original model to these two groups. The results in Figure 12 illustrate that this grouping (i.e., *updated blended method*), as in the original model, results in the highest accuracy, hence validating Result P2.[40] Contrarily, Figure 12 also shows that the overall performance of all heuristics decreases (note the different y-axes). Thus, more cost pools are required to achieve similar accuracy. This again illustrates that the more heterogeneous resource consumption pattern in the ABC cost hierarchy setting requires more information-demanding costing system designs to report accurate product costs. For a comparison, Figure 12 also plots the *blended* method of the original model, which performs worse than the *correlation-rando*m method.[41] Hence, grouping resources before allocating them to cost pools can be detrimental when the groups contain heterogeneous resource consumption patterns. Additionally, the *correlation-random* method achieves similar accuracy as the *updated blended method* with ten cost pools and outperforms the original *blended* method. This is not surprising as it challenges the superiority of the pre-grouping. An explanation may be that introducing the ABC cost hierarchy also provides more structure to the resource consumption from which the correlation-based assignment benefits. More precisely, the improved structure results in stronger positive or negative correlations between different resources' consumption patterns. Hence, grouping resources into cost pools based on their similarity (or dissimilarity) results in more homogeneous resource consumption within a cost pool and more heterogeneous resource consumption between cost pools when a correlation-based assignment is selected.

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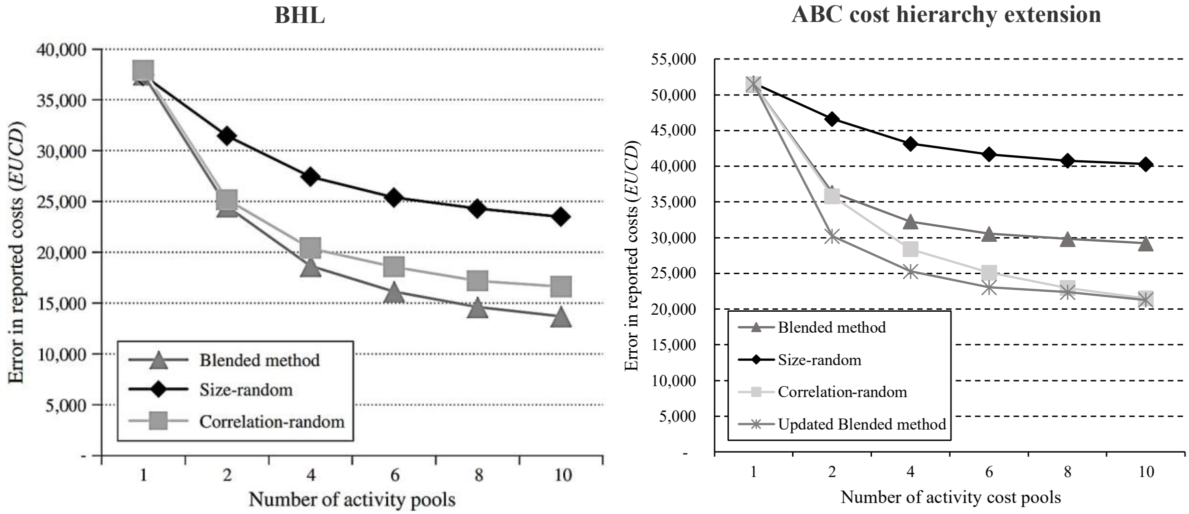
[40] I acknowledge that a heuristic that distinguishes between four groups should perform even better, as it approximates true resource consumption most accurately, by incorporating as many tiers as possible in the implemented ABC cost hierarchy. The implementation of this heuristic, however, would come with some challenges, especially when the number of cost pools is odd or not dividable by the number of groups (tiers). As it is not the objective of this paper to develop further costing system design heuristics, I focus on the simple updated *blended* method, which echoes the same differentiation idea and guide further research to test these more complex heuristics.

[41] To apply the original *blended* method to the four-tier cost hierarchy, I treat unit-level resources as volume-level and all other tiers' resources as batch-level (i.e., non-unit-level).

Figure 12. Robustness analysis of Figure 2 of BHL


BHL

ABC cost hierarchy extension

4.6.2 SELECTING COST DRIVERS

For Figure 3 in BHL, I observe similar offsetting effects on the accuracy of different costing system design heuristics when an ABC cost hierarchy is present. First, Figure 13 Panel A shows that the differences in accuracy between the cost driver selection heuristics are relatively small compared to the original model. Accordingly, selecting a more information-demanding cost driver is less relevant when the *size-random* method assigns resources to cost pools with a present ABC cost hierarchy. Hence, the validity of Result D1 is challenged. Especially when there is only one cost pool in the costing system, the *BIGPOOL* method outperforms all other methods, indicating that a single plant-wide cost driver can perform well in an ABC cost hierarchy-based resource consumption (Horngren et al., 2015).

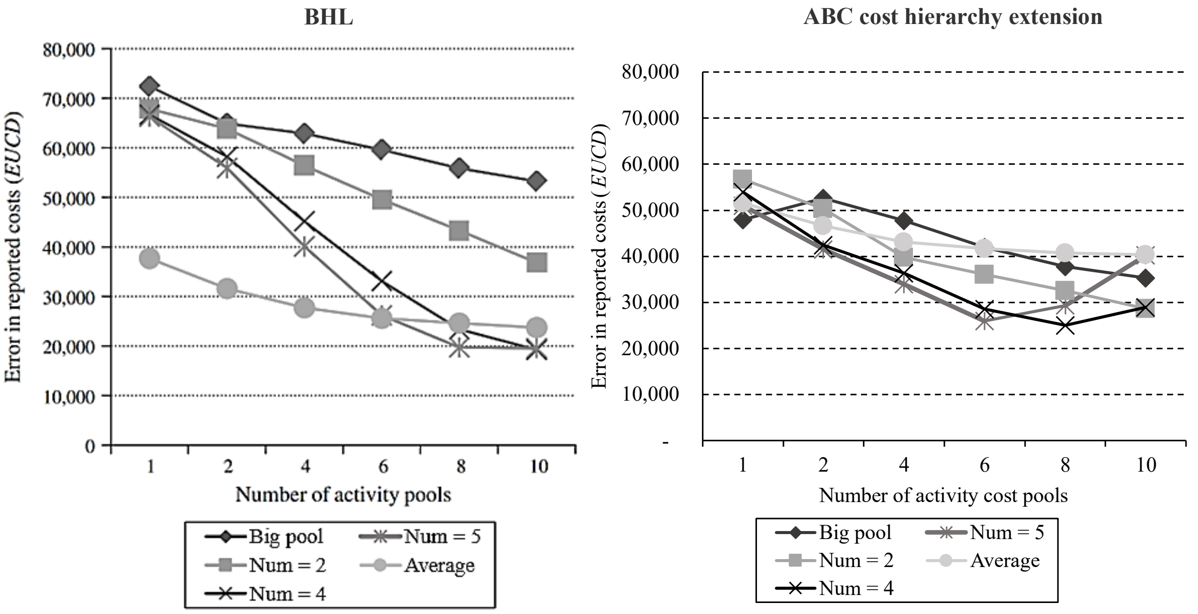
Additionally, the accuracy of the methods *Num4* and *Num5* decreases again when eight or more cost pools are employed in the costing system. This is surprising as it was generally believed that adding more cost pools increases accuracy (Balakrishnan et al., 2011) (Pattern CSD1 from Table 4). I again assume that this effect is caused by decreased offsetting effects for eight or more cost pools. I rationalize this explanation by observing that *Num5* and *Average* yield the exact same accuracy when there are ten cost pools in the costing system. That is because, in the modeled firm with 50 resources, a costing system with ten cost pools contains five resources in every cost pool. *Num5* and *Average* hence compute the exact same cost drivers and result in the same accuracy.

For Panel B of Figure 13, the *BIGPOOL* method is again the most accurate for a single cost pool costing system. However, both Panel A and Panel B show that the error of the *BIGPOOL* method increases and peaks for a costing system with two cost pools. Like the above results, this is due to the offsetting effects when only one cost pool is used. In other words, allocating costs using a single resource's consumption pattern is simple and accurate because differences in other resources' consumption offset one another. Thus, adding the resource consumption of a second resource to allocate costs (e.g., by adding a second cost pool or increasing the information included in the cost driver) may deteriorate the costing system's accuracy.

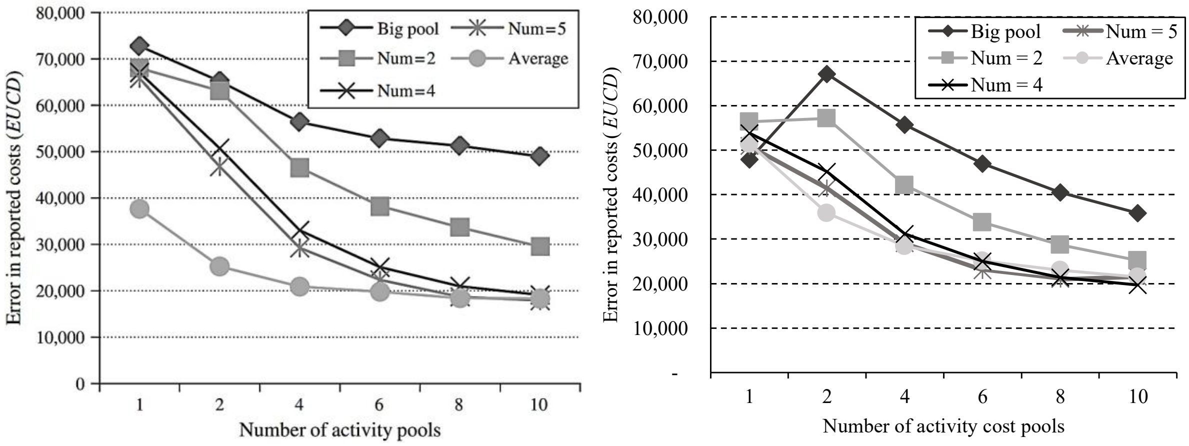
Additionally, Figure 13 highlights that less-information-demanding cost drivers can be more accurate than the information-intensive *Average* cost driver. Panel A shows that the *Average* cost driver performs worst in costing systems with eight or more cost pools. In summary, although not in every respect, the overall recommendation of Result D2 remains valid under these changes in resource consumption.

Figure 13. Robustness analysis of Figure 3 of BHL

Panel A: Use of size-random method to assign resources to activity pools



Panel B: Use of correlation-random method to assign resources to activity pools



4.6.3 INCREASED INFORMATION CONTENT AND OFFSETTING EFFECTS

Incorporating an ABC cost hierarchy in the model has significant yet different effects on the design heuristics concerning the accuracy of reported product costs. Most results from BHL remain qualitatively valid in an ABC cost hierarchy setting, reinforcing their external validity. Contrarily, the results highlight more exceptions to the general understanding that more information-demanding costing systems also result in lower errors in reported product costs (see Figure 2). I assume two different effects of the ABC cost hierarchy are causing these exceptions. First, the ABC cost hierarchy introduces a more structured resource consumption with greater information content from which heuristics that utilize this information (e.g., correlation-based heuristics) benefit (see Figure 12). Second, despite being structured, resource consumption appears also more heterogeneous, with lower or negative correlations between different tiers' consumption patterns (Schmidt et al., 2023). I argue that this benefits the offsetting of errors in very simple costing system designs, achieving higher accuracy than subsequent more refined costing systems (e.g., the single cost pool costing systems in Figure 13). Overall, I corroborate some of the exceptions to the positive relationship between information-demanding costing systems and high accuracy that BHL have already reported. The results also extend this list and contradict some of the findings from BHL. Table 10 summarizes the findings of the robustness analysis. In summary, the robustness analysis tests the external validity of reported results from BHL and stresses some of their limits.

Table 10. Results overview and summary

Result/Finding in BHL	**Description (quoted from BHL p. 540-541)**	**Results** **Close Replication**	**ABC cost hierarchy Extension**
Forming Cost Pools			
Result P1; Figure 1	*When the distribution of resource costs is moderately skewed (top 20% of costs account for less than 40% of total costs), correlation-based methods dominate size-based methods. When the distribution of resource costs is highly skewed (top 20% of costs account for greater than 75% of total costs), size-based methods dominate correlation-based methods.*	Not entirely replicated	The size-random method outperforms correlation-based methods, but the *size-misc* method performs worse than correlation-based methods.
Result P2; Figure 2	*A blended method that groups resources into tiers and uses a size-based rule within each tier results in an error that is comparable to the error obtained with more information intensive methods.*	Replicated	Pre-grouping similar resources before allocating them into cost pools is also beneficial in the ABC cost hierarchy model. However, the pre-grouping must result in homogeneous groups. Otherwise, no pre-grouping and correlation-based assignment performs better.
Result P4; Figure 1	*For all methods assigning resources to cost pools, it is generally preferable to group the costs of low-cost resources into one pool rather than distribute them over the other pools.*	Replicated	This result only holds when resource costs are moderately skewed. If that is the case, a miscellaneous cost pool results in even higher accuracy than the original model. I argue that this is due to the increased offsetting effects.

Table 10 (continued).

Result P5; Figure 1	*A moderate number of cost pools (10–20) seem enough, regardless of the method used to group resources into cost pools. For both size and correlation-based methods, the gain from adding more pools is concave in the number of pools formed.*	Replicated	The increased heterogeneity in the ABC cost hierarchy model increases the demand for more cost pools. However, the reduced marginal utility of adding more cost pools remains. In some settings, more cost pools may even result in worse accuracy.
Selecting Cost Drivers			
Result D1	*In every environment and method for grouping resources into cost pools, an indexed driver is preferred to the "big pool" method of using the consumption pattern for the largest resource.*	Replicated	The *BIGPOOL* method can outperform more information-demanding cost driver selection methods, especially in aggregated costing systems with only one cost pool.
Result D2; Figure 3	*Indexed drivers (using four or five resources) might even do better than the more information-intensive average driver with a moderate (8–12) number of cost pools.*	Replicated	In general, the differences in accuracy between the different cost driver methods can be minor compared to the original model. Therefore, the choice of cost driver is less critical, but instead, it can be detrimental to incrementally improving the cost driver method and result in lower accuracy.

With an ABC cost hierarchy implemented into the model, the results show that simpler costing systems can outperform more information-demanding costing systems. Although BHL already report such exceptions from the traditional intuition that more information-demanding costing systems report more accurate product costs, the model with the ABC cost hierarchy reports even more cases in which this applies. For instance, in the original model, on average, more cost pools and more information-demanding costing systems always lead to more accurate product costs. In contrast, adding more cost pools to very simple costing systems (e.g., single cost pool) decreases the accuracy in the ABC cost hierarchy setting. Overall, this challenges costing system design because the gains in accuracy from incrementally refining a costing system become less linear and less predictable.

I aim to illustrate this challenge by ranking each costing system design depending on the degree of required information. In its simplest form, a costing system consists of one cost pool, with a *random* cost pool allocation method and the *BIGPOOL* method for cost driver selection. In this case, the implementing firm would only require information about its cost-wise largest resource. At the other end of the scale is a costing system with ten cost pools, the *blended* method for grouping costs into cost pools, and an *Average* cost driver. Here, a firm would need to know the cost-wise size of each resource and its respective tier. Moreover, it would need to measure the consumption patterns for all resources to calculate the average cost drivers. In sum, this costing system would be informationally demanding, even though it should result in a better approximation of the true resource consumption and more accurate product costs. I then compare the respective change in accuracy (i.e., *EUCD*) to the simplest costing system when refining the costing system incrementally toward more information-demanding design heuristics (e.g., adding more cost pools or increasing the number of measured resources for the cost driver). A linearly decreasing error along the ranked costing system designs is expected if a more information-demanding costing system always yields gains in accuracy. However, following the results of the robustness analysis, simpler and less information-demanding costing system designs can have a higher probability of benefiting from information content or offsetting effects when an ABC cost hierarchy is present. In these cases, the gain in accuracy is expected to be less linear and may even yield increased errors if this assumption holds.

I explore the effect of incrementally refining the costing system design in two settings with different information-demand scores. For the first setting (Panel A of Figure 14), I include all design parameters of costing systems – number of cost pools, allocation heuristics, and cost driver selection heuristics into calculating the information demand score. I base the scores on the description in BHL of how information-demanding each design parameter is. Table 11 overviews the scores for each of the CP-Heuristic. Adding another cost pool requires an added cost driver and, hence, more information that needs to be obtained by the costing system (the score of required information increases proportionally to the number of cost pools). Likewise, increasing the number of resources combined in a cost driver (*BIGPOOL* vs. *Indexed* vs. *Average*) also increases a costing system's information demand (the score of required information increases by one point). It is unclear which heuristics require more information for the cost pool allocation heuristics. For this, I oriented along the explanations from BHL to assign these scores and varied them to test the robustness of the associated findings. Additionally, note that the ranking is based on an ordinal scale. That means that the absolute score of a costing system is less important than its relative position compared to a simpler or more information-demanding costing system on that scale.

Table 11. Information-demand score for the number of cost pools and each heuristic

Number of Cost Pools	Score	CP-Heuristic	Score	CD-Heuristic	Score
1	1	*Random*	0	*BIGPOOL*	0
2	2	*Size-random*	1	*Num2*	1
4	4	*Size-misc*	1	*Num4*	2
6	6	*Correlation-random*	2	*Num5*	3
8	8	*Correlation-size*	3	*Average*	4
10	10	*Blended*	4		

Note. I employ the b*lended* method as described in BHL for the original model and the *updated blended* method for the ABC cost hierarchy model.

Compared to the *random* method, the *size-random* and *size-misc* methods require knowledge of the largest resources and their resource consumption. They are, therefore, more information-demanding than pure random assignment. Next, c*orrelation-random* requires correlation information for different resources’ consumption patterns. Additionally, c*orrelation-size* further requires knowledge about the largest cost-wise resources. Finally, the *blended* method requires knowledge about the different tiers and consumption patterns in the firm’s true resource consumption. For the *CD-Heuristics*, the indexed drivers *Num2*, *Num4*, and *Num5* measure an increasing number of resource consumption patterns to construct the cost driver. They are, therefore, increasingly demanding of information, with the *Average* driver being the informationally most demanding cost driver heuristic.

The second setting (i.e., Panel B of Figure 14) shows an information-demand score based on the number of cost pools and cost driver selection heuristics. Thus, the potentially subjective evaluation of information demand scores for the *CP-Heuristics* is left out to obtain a more robust score.[42]

Both panels in Figure 14 show the gains in accuracy compared to the simplest costing system for both models – the original and the ABC cost hierarchy extension. First, Figure 14 shows that the accuracy decreases along all degrees of costing systems. I suspect this is due to the increased heterogeneity in the resource consumption matrix.

Second, both panels illustrate that the gain in accuracy from increasing the information demand is more concave with the ABC cost hierarchy extension compared to the original model.

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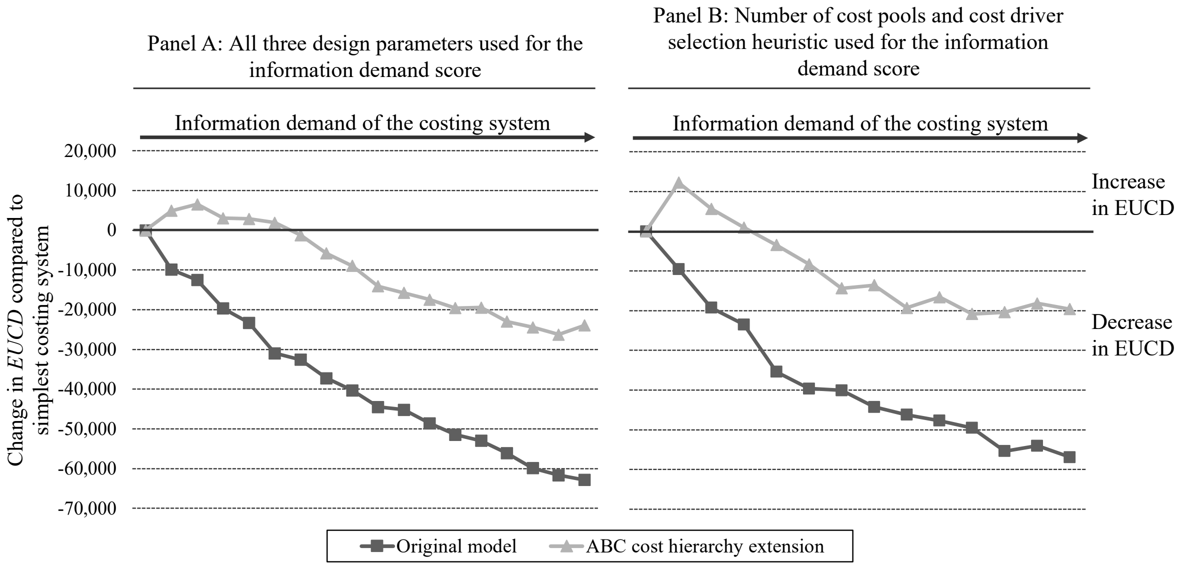
[42] Additionally, I calculate two further information-demand scores in the appendix of this thesis (Chapter 9.2) to validate the robustness of this analysis and find that the qualitative results hold under these changes.

Although it has been noted previously (Balakrishnan et al., 2011; Friedl, Hofmann, & Pedell, 2017), the marginal utility of refining the costing system may be even smaller.

In the original model, there is a relatively linear decrease in *EUCD*, wherefore incremental refinements in the costing system yield similar payoffs in accuracy. Contrarily, for the ABC cost hierarchy model, Figure 14 depicts a significantly less linear pay-off for both information-demand scores. More precisely, the results show that for the first third of refinements from the simplest system, the accuracy decreases. Consequently, there is a high probability for simple costing systems to outperform subsequent, more information-demanding costing systems. Next, incremental refinements pay off for the medium third of information-demanding costing systems (i.e., steep, and linear downward curve progression). Finally, for the upper third of information-demanding costing systems, additional gains in accuracy decrease as the curves' decline decreases. This is especially the case in Panel B of Figure 14.

Figure 14. Change in accuracy (EUCD) when incrementally increasing the information demand of the costing system



Note. EUCD = Euclidean Distance between benchmark and reported product costs for all products in the portfolio.

I understand that implementing the ABC cost hierarchy in the modeled production environment's resource consumption increases its heterogeneity and structure. That is, the true resource consumption is segregated into four tiers – compared to two tiers in the original model – while each tier contributes different shares of resources and costs to the total costs that need to be allocated accurately. I expect specific costing system designs to benefit from this updated resource consumption pattern by exploiting the increased informational content through the more structured resource consumption. Additionally, the ABC cost hierarchy increases the potential for more offsetting than in a two-tier hierarchy (Datar & Gupta, 1994). Offsetting effects in cost allocation describe that overstated and understated consumption measurements in different cost drivers of the costing system cancel each other out so that reasonable accuracy is achieved for the final product costs (Datar & Gupta, 1994). Very simple costing systems can benefit from this by leveraging these offsetting effects.

Few prior studies have reported on offsetting effects in cost allocation. Datar and Gupta (1994) and Gupta (1993) report on case studies and simulation experiments that offsetting effects are generally likely in costing systems as different errors may cancel out one another. Labro and Vanhoucke (2007) specify these findings and note that incrementally improving a costing system usually pays off in higher accuracy, while there are exceptions for highly aggregated costing systems. The findings of this chapter substantiate these exceptions as I observe several cases where less information-demanding, very simple costing system designs outperform subsequent more information-demanding designs at times, making accuracy gains less predictable. Collectively, these results suggest that, from an accuracy perspective, it can be beneficial for firms to stick to very simple costing systems and avoid being stuck in the middle. Achieving more accurate costing systems requires more than incremental refinements.

4.7 CONCLUSION AND DISCUSSION

This chapter aimed to test the internal and external validity of costing system design heuristics concerning the accuracy of reported product costs, as reported by Balakrishnan et al. (2011). First, to test the internal validity of the results, I closely replicated the simulation model and experiments of the original paper. The replication results show high internal validity for the majority of findings. I only find one exception where the replicated results are less aligned with the original paper's.

Second, I tested external validity by conducting a robustness analysis by implementing an ABC cost hierarchy in the resource consumption of the underlying production environment. This approach systematically changes the resource consumption patterns whereby the design heuristics of the costing system design may be affected. I formulate theoretical expectations for the expected effects. The results of the robustness analysis indicate that, again, many results from the original paper remain valid. However, I observe recurring effects that challenge some of these results and corresponding rules. In particular, offsetting effects within the costing system – when the ABC cost hierarchy is present – may be more relevant than previously assumed in the original model (Datar & Gupta, 1994; Labro & Vanhoucke, 2007). This generally indicates that incremental refinements in costing system design infrequently result in accuracy payoffs. In addition, certain heuristics (e.g., *updated blended*) benefit from the more structured resource consumption in the ABC cost hierarchy. Overall, these results frame the external validity of results concerning costing system design heuristics.

This chapter contributes to the discussion of replication in accounting research (Basu & Park, 2014; Salterio, 2014; Shields, 2015). While the debate mainly centers around empirical methods, the here conducted analysis complements these methods with a computational social science perspective. More specifically, it aims to highlight the importance of testing the validity of results from simulation experiments, as their validity can be limited by implementation specifications of the original model and by assumptions made in the model's design.

Moreover, the results add to the discussion of the presence of an ABC cost hierarchy as I illustrate the effects that this hierarchy may have on costing system design heuristics. In this regard, I show how costing system design refinements are far less linear than expected, which results in a higher probability of very simple costing systems being more accurate than increasingly information-demanding costing systems. I understand this as an additional explanation for the low adoption rate of complex costing systems, such as ABC (Gosselin, 2006), and, in turn, the high adoption rate of very simple costing systems (Al-Omiri & Drury, 2007; Drury & Tayles, 2005), which the literature frames as the "ABC-Paradox" (Cinquini et al., 2015; Gosselin, 2006). Hence, this chapter also adds to the concept of costs of costing systems (see Figure 2), which describes a trade-off between the costs of errors from inaccurate costing systems and the costs of implementing and maintaining more information-demanding costing systems. In that regard, the results indicated important exceptions from that rule that potentially can be exploited to achieve high accuracy with low implementation costs.

Next, the results also show that with an ABC cost hierarchy, the benefits of incremental refinements toward a more complex costing system are less straightforward. Incremental refinements can also reduce accuracy. Prior accounting research often compares very simple and very complex costing systems with each other (Banker & Potter, 1993; Duh et al., 2009; Shank & Govindarajan, 1988) and neglects in-between designs. I follow Labro and Vanhoucke (2007) by closing this gap and disentangling in-between costing system designs and the effect of incremental refinements. I show how incremental refinements from very simple costing systems can also reduce accuracy, with managers risking being stuck in the middle. By doing so, the analysis in this chapter also contributes to education and practice. It informs costing system designers to be cautious when making costly improvements to their costing system design. More specifically, the shown results concerning costing system design address the two prominent patterns that more cost pools (CSD1) and more sophisticated cost drivers (CSD2) decrease the system-level error (see Chapter 3) and illustrate that although these relationships hold in many settings, there may be important limitations. Thus, I provide an updated picture of the comparison between different design heuristics under a present ABC cost hierarchy to support practice in designing costing systems.

Finally, the analysis in this chapter also has limitations, which may provide fruitful avenues for future research. First, I emphasize the importance of code and data sharing. Although the replicated model could reproduce many findings, some discrepancies in the code and results could not be fully explained. Second, although I derive the modeling approach from prior analytical and empirical studies, literature and empirical data about costing systems and resource consumption in firms (including the ABC cost hierarchy) are sparse. This limits the validity of corresponding numerical experiments and modeling approaches. Accordingly, more empirical research in this avenue could validate simulation results further. Third, to increase the external validity of the results, I implement an ABC cost hierarchy, although there are several other ways to test external validity. The cost accounting literature often demands testing the influence of non-linear resource consumption on costing system design rules (Christensen, 2010; Labro, 2019). Engineering literature observes that different product designs (Davila & Wouters, 2004) or product variety management strategies (Erens & Verhulst, 1997) shape resource consumption patterns. Thus, they most likely also affect costing system design efficacy. Investigating the effects of these concepts on costing system design may be rewarding for further research projects.

5 INVESTIGATION OF THE VBC VOLUME-BIAS BASED ON A MODEL REPLICATION OF ANAND ET AL. (2019)[43]

5.1 INTRODUCTION

One of the most prominent patterns of errors in cost information is the VBC volume-bias (CSB1 in Table 4). It is often framed as one of the major reasons for the development of ABC (Cooper & Kaplan, 1999) and has important practical implications for firms. More specifically, cost-based pricing tends to distort selling prices due to this pattern: high-volume products would be too expensive, while low-volume products would be too cheap (Shank & Govindarajan, 1988). As a result, the demand for high-volume products might decrease, while low-volume products do not generate enough profit. Overall, this adversely affects a firm's competitiveness and profitability, illustrating the economic relevance of this pattern. Prior studies suggest that the pattern arises in volume-based costing systems when the underlying resource consumption not only varies with production volumes but also with other decoupled activities (e.g., batch-related or product-sustaining activities) (Cooper & Kaplan, 1991). Despite this importance, large-scale computational experiments have not yet investigated the VBC volume-bias pattern (CSB1, Table 4).

The objective of this chapter is to examine the occurrence and mechanism of the VBC volume-bias pattern (CSB1) based on a model replication of the simulation model from Anand et al. (2019) (ABL framework from here).

Similar to the approach in Chapter 4, I aim to replicate the ABL framework to ensure the internal validity of results produced by the model. Since Anand et al. (2019) do not provide results in their paper, I use three patterns from Table 4 (CSD1, RC3, CSB3) as reference results to test the replication’s success. Next, I extend the ABL framework by altering the underlying resource consumption of the modeled production environment to examine whether non-unit-level resource consumption or an ABC cost hierarchy (see Chapter 2.3), in combination with a

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[43] This chapter is based on Schmidt, M., Mertens, K. G., & Meyer, M. (2023). Cost hierarchies and the pattern of product cost cross-subsidization: extending a computational model of costing system design. PLOS ONE, 18(9). doi: 10.1371/journal.pone.0290370. More precisely, the majority of results from this chapter are based on the paper but are adapted and extended by additional analyses that are not in the published paper and stem from prior unpublished versions or the paper’s appendix. This applies to the chapters from page 84 to page 115, including figures and tables.

VBC system, produces the VBC volume-bias pattern. Understanding the precise mechanism behind the VBC volume-bias pattern allows firms to undertake countermeasures to account for this pattern.

The replication results confirm the successful replication of the ABL framework. I document relational and distributional equivalence between the original and replicated models and observe that the general model behavior holds in the replicated model. In more detail, I document the reproducibility of the three patterns drawn from prior research (CSD1, RC3, CSB3 - Table 4). Concerning the second objective, the results show that the unchanged ABL framework does not reproduce the product VBC volume-bias cross-subsidization pattern, indicating that it does not incorporate the mechanism behind it. However, by extending the model with a cost hierarchy comprising non-unit-level resource consumption and volume-based cost drivers, the model can reproduce the pattern, which allows it to specify its likely mechanism based on a large-scale computational experiment. Eventually, I corroborate this mechanism by implementing a full four-tier ABC cost hierarchy and show that an increased alignment between non-unit-level costs and unit-level cost drivers diminishes the pattern. The extensions made to the model in this chapter further strengthen its ability to investigate the real-world system under investigation (i.e., empirical cost accounting). Therefore, the analysis in this chapter adds relevant insights to the simulation model's validity and this thesis's overall objective.

5.2 PRIOR CONSIDERATIONS

To achieve the described objectives, I pursue two steps: first, I replicate the ABL framework; second, I subsequently investigate the VBC volume bias in product cost cross-subsidization. Similar to the approach in chapter 4, I follow the suggestion of Thiele and Grimm (2015) to reuse and leverage existing models and to guide the model analysis with recurring patterns (Grimm & Berger, 2016a; Grimm et al., 2005). Hence, a replication is imperative to increase the validity of the computational model's scientific claims, verify the model's usability for future studies, and reproduce the findings of this model and its predecessors (Balakrishnan et al., 2011; Homburg et al., 2018).

The first objective of this chapter is to replicate the ABL framework. The ABL framework includes design rules to test choices on costing systems regarding the provided accuracy in cost information and includes model components and results from prior research (Anand et al., 2017; Balakrishnan et al., 2011; Labro & Vanhoucke, 2007, 2008). This makes the framework a potential standard approach for future studies on costing system design to scrutinize remaining challenges in literature and practice. Based on the original model's conceptual model (model description in the original paper's appendix)[44] and implementation, I closely replicate the ABL framework by implementing it in a new software environment. I follow prior approaches to computational model replication (see Chapter 2.5) and adopt best practices (Axtell et al., 1996; Wilensky & Rand, 2007) and guidelines (Burman et al., 2010; Thiele & Grimm, 2015). To focus the analysis of the replication, I follow the strategy of pattern-oriented modeling (Grimm & Berger, 2016a; Grimm et al., 2005; Thiele & Grimm, 2015) since the original study from Anand et al. (2019) does not provide results to orientate on. Patterns are here defined as descriptions of specific relations between input and output variables (Heine et al., 2005) (see Chapter 2.6). I draw on three patterns in errors in cost information from Table 4, namely Cost Pool Relationship (CSD1), Degree of Resource Sharing (RC3), and Dominant Undercosting (CSB3). I scrutinize whether profound differences exist between the original and replicated models regarding the relation described by the pattern.

The second objective of this study is to employ the replicated model to investigate the mechanism behind the VBC volume bias pattern (CSB1). The pattern describes that a costing system overcosts high-volume products and undercosts low-volume products (Cooper & Kaplan, 1988a) and is, therefore, a bias in product-cost cross-subsidization (also see Chapter 3.3). Cooper and Kaplan (1988b) are the first to note that overhead costs are often not proportional to production quantities. They therefore propose ABC ought to recognize and account for non-unit-level (i.e., production quantity independent) resource consumption. They believe this is a requirement to prevent the VBC volume bias in product cost cross-subsidization.

To support their claim and their newly proposed cost allocation approach, Cooper and Kaplan – in a series of publications (Cooper, 1988b; Cooper & Kaplan, 1988a, 1988b, 1991, 1999; Kaplan & Cooper, 1998b) – propose the subdivision of a manufacturing firm's resource consumption into four tiers, which they denote as the "ABC cost hierarchy": unit-level, batch-level, product-sustaining-level and facility-sustaining-level costs (see Chapter 2.3). As in volume-based costing systems, allocating costs based on unit-level activities would result in the described product cost cross-subsidization pattern (Cooper & Kaplan, 1991). Therefore, ABC is expected to diminish the pattern because it employs cost drivers from all tiers of the cost hierarchy. However, several surveys still report high usage of simple volume-based costing systems (Al-Omiri & Drury, 2007; Gosselin, 2006) (also see Chapter 9.1 in the appendix). Thus,

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[44] The appendix of the ABL framework can be found here: https://github.com/vanand74/CostSystemSim.

understanding the mechanism behind product cost cross-subsidization in VBC systems and the resulting VBC volume bias is highly relevant for many firms.

Prior analytical and simulation-based research investigated costing errors and resulting product cost cross-subsidization but primarily focused on ABC systems. However, these studies did not consider VBC systems. One prior study that focuses on VBC is Hwang et al. (1993). The authors develop a numerical example based on an analytical model to study antecedents of over- or undercosting biases in product costs. Although they provide relevant insights into cross-subsidizing product costs, their employed numerical example is limited to two products and simple production environments. Other simulation studies (Balakrishnan et al., 2011; Labro, 2006a) measure the system-level error of a costing system as their primary dependent variable and do not focus on product cost cross-subsidization in their analyses (i.e., product-level error). In summary, previous analytical and simulation studies provide a strong basis for modeling various production environments and costing systems. However, since they lack detail or generality, they do not adequately explain the mechanism behind the observed pattern of cross-subsidization of product costs in VBC systems. Following Grimm et al. (2005) I employ a pattern-oriented modeling approach to develop a computational model with greater structural realism by implementing VBC systems and non-unit-level resource consumption into the model.

5.3 MODEL DESCRIPTION AND REPLICATION APPROACH

5.3.1 Introduction of the Numerical ABL Framework[45]

The computational model from the ABL framework consists of two main components: the firm in the form of a production environment and the firm’s costing system. The production environment specifies how resources are used to produce products or services (i.e., true resource consumption). The model's objective is to contrast the benchmark of a full information setting of production environments with limited information settings of various costing systems,

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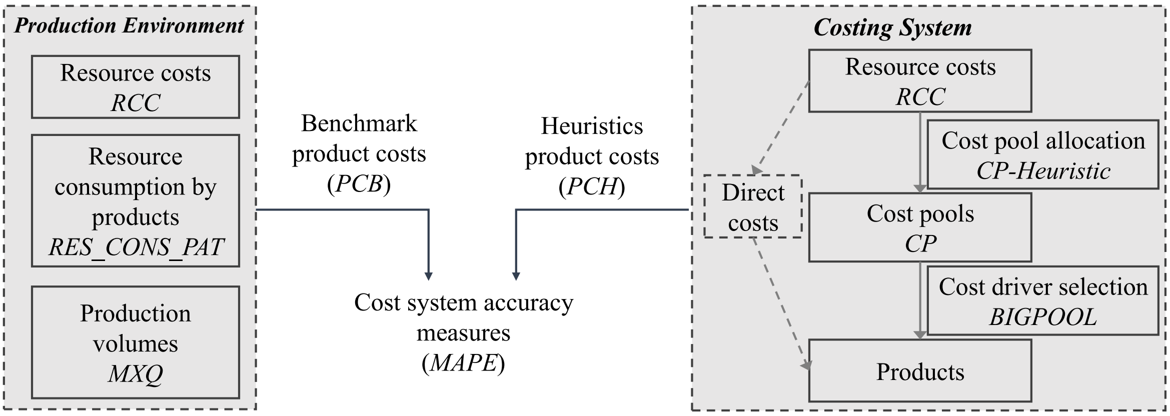
[45] Since the ABL framework from Anand et al. (2019) is based on the model from Balakrishnan et al. (2011), which is employed in Chapter 4 of this thesis, the two models are very similar. Nevertheless, there are several important differences in the modeling. To compare the two models, I will fully describe the ABL framework. Major differences are in the cost pool allocation heuristics (*CP-Heuristic*) and the presence of production volumes in the ABL framework. Especially the latter profoundly affects the mechanics behind the generation of both benchmark (*PCB*) and reported product costs (*PCH*).

thereby allowing the calculation of errors in reported cost information. Figure 15 conceptually illustrates the two main components of the computational model.

Figure 15. Conceptual illustration of the computational model



Note. *RCC* = Vector of resource costs; *RES_CONS_PAT* = Resource consumption pattern matrix; *MXQ* = Vector of production volumes; *PCB* = Benchmark product costs; *CP-Heuristic* = Heuristic used for allocating resource costs to cost pools; *CP* = Cost pools; *BIGPOOL* = Heuristic used for selecting cost drivers; *PCH* = Heuristics' (reported) product costs; *MAPE* = Mean absolute percentage error.

The first component of the computational model – *the production environment* – is the firm's full information setting that resembles all resource usages of all products and their production volumes (*MXQ*) in a resource consumption matrix (*RES_CONS_PAT*). The matrix has as many columns as resources (*NUMB_RES*) and as many rows as products *(NUMB_PRO*). Hence, every entry y_{ij} resembles the usage of resource *j* by product *i*. Since every resource has its costs, the model computes resource costs (*RCC*) from the *RES_CONS_PAT*. User-defined settings randomly draw all parameters. *MXQ* is drawn from a uniform distribution, with user-specified boundaries to reflect differently heterogeneous production quantities, represented by *Q_VAR*. The resource cost vector (*RCC*) consists of "big" and "small" resources. The input parameter *DISP2* defines the "big" resources' share of the total costs (*TC*), whereas *DISP1* indicates the number of "big" resources, which must not exceed the total number of resources (*NUMB_RES*). Subsequently, a high *DISP2* value and a low *DISP1* value resemble disparate resource costs, with a few "big" resources accounting for a large proportion of the total costs (*TC*). The *RES_CONS_PAT* links production quantities and resource costs. The input parameters *DENS*, *COR1*, and *COR2* generate resource consumption heterogeneity in the *RES_CONS_PAT* matrix. *DENS* defines the number of non-zero entries in the matrix, reflecting the degree of resource sharing. For example, a value of 0.2 sets approximately 20% of *RES_CONS_PAT* to be non-zero, meaning that products share only a few resources, for example, in a workshop environment (Balakrishnan et al., 2011). The correlation parameters set the similarity between resource consumption for two parts of the matrix, aiming to reflect two different tiers in the cost hierarchy, such as unit-level and batch-level resources (Ittner et al., 1997). Therefore, high *COR1* and *COR2* values induce product similarity through highly correlated resource consumption. Low values increase the disparity, e.g., meaning that products become dissimilar (Anand et al., 2023). If all information is available about production volumes (*MXQ*), resource consumption (*RES_CONS_PAT*), and resource costs (*RCC)*, the benchmark costs of a cost object (*PCB*) can be calculated by multiplying a relative resource consumption (*RES_CONS_PATp*) for every resource by every product with the resource costs from *RCC*.

$$PCB = RES\_CONS\_PATp\ * RCC \tag{1}$$

The second component of the model – *the costing system* – only obtains limited information from *RES_CONS_PAT* and then calculates the costs of the final cost objects. The costing system is a two-stage allocation system (Labro & Vanhoucke, 2007) (see Chapter 2.1). First, resource costs are pooled in a selected number of cost pools using a cost-pool-allocation heuristic (*CP-Heuristic*). Cost pools (*CP*) contain the pooled resource costs. Second, every cost pool requires an allocation base, called a cost driver, using a cost-driver selection heuristic (*CD-Heuristic*). The allocation base is the resource consumption of a selected resource. It allocates the cost pool costs to the final cost objects, such as products, customers, or distribution channels. The choice and functionality of costing system design heuristics (*CP-Heuristic* and *CD-Heuristic*) in the two-stage allocation system significantly affect the errors in reported product cost information (see Chapter 4).

The original model has four different heuristics for the assignment of resource costs to cost pools, which are described in more detail in the online appendix of the ABL framework:

1) *Size-Miscellaneous* (*SM*): In a setting with m cost pools, the (m-1) largest resources are assigned to one cost pool each. The remaining resources are allocated in the last cost pool (i.e., miscellaneous cost pool, "*miscpool*").
2) *Size-Correlation-Miscellaneous* (*SCM*): In a setting with m cost pools, the (m-1) largest resources are assigned to one cost pool each. All remaining resources are assigned to these same (m-1) cost pools based on how much they correlate to the seeded resources. Once the total value of the unassigned resources falls below a defined amount of monetary units (*MISCPOOLSIZE*) or the correlation value (*CC*) falls below a defined threshold, all remaining resources are pooled in a miscellaneous pool.
3) *Size-Random-Miscellaneous* (*SRM*): The (m-1) largest resources are assigned to (m-1) cost pools. The rest of the resources are then randomly assigned to cost pools until the

total monetary value of the unassigned resources falls below a defined amount of monetary units (*MISCPOOLSIZE*). Once this happens, all remaining resources are pooled in a miscellaneous pool.

4) *Size-Correlation-Miscellaneous-CutOff* (*SCMC*): The largest resource is allocated to a cost pool, then further resources are allocated to this cost pool if their correlation is larger than *CC*. This is repeated for the following cost pools. If there are as many remaining resources as unfilled cost pools, every remaining cost pool is filled with one resource. If more resources are unassigned than empty cost pools and *MISCPOOLSIZE* is reached, every remaining cost pool, except the last, is filled with one resource, and the *miscpool* is filled with the remaining resources.

The *BIGPOOL* method selects a cost driver by defining the largest resource within a cost pool as the cost driver. Because the costing system only obtains a subset of the resource consumption matrix (*RES_CONS_PAT*), it only approximates the full resource consumption. This subset is defined as the activity consumption matrix (*ACT_CONS_PAT*). Each row in *ACT_CONS_PAT* provides the measured resource consumption of the costing system for each cost object and cost pool. Consequently, *ACT_CONS_PAT* has as many columns as the number of cost pools (*CP*). For each cost pool *CP*, the sum of the allocated resource costs is known (e.g., from financial accounting (Balakrishnan et al., 2012a)). Hence, multiplying the relative resource consumption of every entry with the respective dollar amount allocated in each *CP* provides the occurring costs of each cost object. Summing over the entries for each row provides the reported costs of the cost object (*PCH*) by the costing system.

$$PCH = ACT\_CONS\_PATp \; * CP \tag{2}$$

As the last step, the Mean Absolute Percentage Error (*MAPE;* see Table 1) between *PCB* and *PCH* of every product i is calculated to evaluate the resulting errors in product costs for different costing system designs and production environments.[46]

5.3.2 REPLICATION OF THE COMPUTATIONAL MODEL OF THE ABL FRAMEWORK

The first objective of this study is to replicate the computational model of the ABL framework. The ABL model provides a ready-to-use framework for future research, even though the original paper does not document results. To address relational equivalence, I first conduct a broad numerical experiment – following the 3k-design of experiments – in which I vary all relevant parameters (Lorscheid et al., 2012) in low, medium, and high specifications. Using an

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[46] Table 29 in the appendix (Chapter 9.5) overviews descriptions of all modeled variables and relevant technical terms.

OLS regression model containing the relevant variables, this analysis compares their effects on costing errors (*MAPE*) in both models to evaluate relational equivalence. Second, to assess distributional and numerical equivalence between the two models, I focus on the three named patterns of errors in cost information to obtain a relevant perspective on the computational model's results (Grimm et al., 2005; Thiele & Grimm, 2015). Chapter 2.5 contains a detailed description of a pattern-oriented replication approach.

Table 12 shows the conducted numerical experiment with all relevant input, control, and output variables and the factor ranges and levels for the 3k experiment. The conducted 3k-design parameter setting ('Low'; 'Middle'; 'High') upscales the standard 2k-design of ABL ('Low'; 'High') by evenly separating the parameter range into the three segments. This has the advantage that non-linear effects can be detected (Lorscheid et al., 2012). Additionally, for replication purposes, the experiment includes the full range of possible cost pools (i.e., 1 to 50) and all cost pool allocation heuristics (*CP-Heuristic*) to gain a complete picture of the boundaries. I generated 32,076 design points (i.e., unique parameter combinations) with 729 unique production environment parameter combinations and 44 different costing systems. Combined with the 200 randomly generated production environments (*NUMB_FIRMS*) as described in Anand et al. (2019), I obtained 712,800 total observations. This experiment is conducted for both the original and replicated model.

Table 12. Design of experiments of the replication experiment of the ABL framework

Input variables		**Control variables**		**Output variables**
Production Environment				
COR1 Correlation between volume resources	U[-0.8,0.8]	*NUMB_PRO* Number of products	50	*MAPE* Mean Absolute Percentage Error
COR2 Correlation between batch resources	U[-0.8,0.8]	*NUMB_RES* Number of resources	50	*BE_AB* Difference between share of materially overcosted and share of undercosted products
DENS Density of RES_CONS_PAT	U[0.2,0.9]	CC Correlation Cut-off variable	0.4	*PCB* Benchmark costs of a cost object
Q_VAR Disparity in production quantities	U[10,20]; U[10,40]; U[10,60]	*MISCPOOLSIZE* Relative share of costs in MISCPOOL	0.25	*PCH* Heuristics costs of a cost object

Table 12 (continued).

DISP1 Number of "big" resources	2;5;10	*TC* Total Costs	1.000.000	*MXQ* Production quantities per product
DISP2 Share of costs that are assigned to the "big" resources	U[0.2,0.9]	*NUMB_FIRMS* Number of runs for every input variable combination for the production environment	200	Percentage Error (*PE*) *PE* = (*PCH* – *PCB*)/*PCB*
Costing System				
CP Number of Cost Pools	1,5,10,15,20,25, 30,35,40,45,50			
CP-Heuristic Heuristic to allocate resources into cost pools	*SM*, *SCM*, *SRM*, *SCMC*			
CD-Heuristic Heuristic for cost-driver selection	*BIGPOOL*			

Note. Design points = 11*3*3*3*3*3*3*4 = 32,076 (i.e., unique parameter combinations), 712,800 observations.

5.4 REPLICATION RESULTS

To evaluate replication success, I compare the replicated model with the original model based on the parameters' effects on the system-level error in reported cost information (*MAPE*). Because the different cost pool allocation heuristics (*CP-Heuristic*) result in different costing systems, I split the data set accordingly and conduct an OLS regression for each heuristic. Note that the dependent variables of the regression analyses are not normally distributed, which is not unusual for simulation models (Fachada et al., 2017). According to the literature, the normality of the dependent variable is not always required to obtain accurate and unbiased estimates in regression analyses, particularly when the sample size is large (Lumley et al., 2002; Schmidt & Finan, 2018). Nonetheless, to ensure the robustness of the results, I conducted two additional analyses. First, I performed robustness analyses on the regression coefficients with transformations of the dependent variable. Second, I employed a bootstrapping approach for significance testing to address the underlying non-normality. Untabulated results show that the findings of this experiment remain consistent after both robustness tests. Table 13 provides an overview of the regression analyses for each cost pool allocation heuristic *CP-Heuristic*.

Table 13. Relational equivalence for all parameters

	SM		SCM		SRM		SCMC	
	ORIGINAL	*REPLICATION*	*ORIGINAL*	*REPLICATION*	*ORIGINAL*	*REPLICATION*	*ORIGINAL*	*REPLICATION*
Production Environment								
DISP1	0.14**	0.13**	0.11**	0.09**	0.09**	0.09**	0.09**	0.09**
DISP2	-0.37**	-0.37**	-0.31**	-0.27**	-0.27**	-0.28**	-0.24**	-0.24**
DENS	-0.24**	-0.25**	-0.27**	-0.29**	-0.29**	-0.30**	-0.23**	-0.24**
COR1	0.00	0.00	0.00	0.00	0.00	0.00	0.01**	0.00
COR2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Q_VAR	0.00	0.00	-0.03**	0.00	0.00	0.00	-0.04**	-0.04**
Costing System								
CP	-0.74**	-0.74**	-0.77**	-0.83**	-0.82**	-0.82**	-0.76**	-0.75**
Adj. R^2	.764**	.763**	.783**	.847**	.848**	.845**	.695**	.691**
N	178,200	178,200	178,200	178,200	178,200	178,200	178,200	178,200

Note. Dependent variable: Mean absolute percentage error (*MAPE); CP* = Number of cost pools*; DISP1* = Number of “big” resources*; DISP2* = Share of costs that are assigned to “big” resources*; DENS* = Degree of resource sharing*; COR1*= Correlation between volume resources*; COR2* = Correlation between batch resources*; Q_VAR* = Disparity in production volumes*;* Presented β coefficients are standardized; * indicates p < .05. ** indicates p < .01.

First, I note that the adjusted R^2 for three of the four heuristics is nearly similar between the original and replicated models. Only for the heuristic *Size-Correlation-Miscellaneous* (*SCM*) does the regression of the replicated model explain more of the total variance, showing a greater difference between the two models. Second, the two models have two smaller differences in significance levels. For the heuristic *Size-Correlation-Miscellaneous-CutOff* (*SCMC*), *COR1* has a small significant positive effect on *MAPE*. This effect is, however, only present in the original model. Using the heuristic *Size-Correlation-Miscellaneous* (*SCM*), the disparity in production volumes (*Q_VAR*) significantly affects *MAPE* only in the original model (-0.03**) but not in the replicated model. Apart from this, the significance levels are equal for all parameters.

Finally, there are differences at the level of magnitude (e.g., *Size-Correlation-Miscellaneous* (*SCM*) – *DISP1* (original): 0.11**, *DISP1* (replication): 0.09**). There are, however, no changes in the direction of effects between the models. Thus, following Belding (2000) that complete equivalence of the original and replicated models is barely possible in stochastic simulations, the results suggest that the replicated model's implementation is relationally but not yet numerically equivalent to the original model's implementation.

To guide the assessment of distributional equivalence, I draw on the three well-documented patterns and compare the results of the original and replicated models. The three patterns are: CSD1 - Cost Pool Relationship - *A greater number of cost pools decreases the system-level error* (Balakrishnan et al., 2011; Labro & Vanhoucke, 2007), RC4 - Degree of Resource Sharing - *A lower degree of resource sharing increases system-level errors* (Gupta, 1993; Kerremans et al., 1991) and CSB3 - Dominant Undercosting - *In ABC systems more products are being under- than overcosted* (Christensen & Demski, 1997) (see Chapter 3 for a detailed description).

The perspective on single patterns allows for a more fine-grained analysis of the replication's success at the level of distributional equivalence. I compare the moments of the distribution of the output variable (i.e., mean, standard deviation, skewness, and kurtosis) for each pattern to evaluate statistical alignment that satisfies distributional equivalence. I purposefully avoid statistical power tests, such as the Kolmogorov-Smirnov test (Axtell et al., 1996), because statistical tests can be over-sensible with large sample sizes (Secchi & Seri, 2017; White et al., 2014). This applies to the here conducted numerical experiment with 712,800 observations. To support this selection, I generate increasing sample sizes randomly drawn from the total data set of the numerical experiment and compare the p-value of the Kolmogorov-Smirnov-Test and the average deviation in regression coefficients (as in Table 13) for each sample size. Chapter 9.4 in the appendix shows this comparison and highlights that the two criteria behave anti-proportional. Hence, the Kolmogorov-Smirnov-Test can be misleading when assessing distributional equivalence.

5.4.1 COST POOL RELATIONSHIP – CSD1

Cost accounting literature suggests that a costing system design with more cost pools captures resources in more detail with more allocation bases (Drury & Tayles, 1994; Horngren et al., 2015) and thus decreases the system-level error.[47] I examine this relationship in the model's results by measuring the *MAPE* along with an increasing number of cost pools. This allows for observing whether more cost pools result in a lower system-level error, as indicated by a lower *MAPE*. Figure 16 depicts the MAPE for different numbers of cost pools.

Table 14 lists the mean, standard deviation, skewness, kurtosis, and the absolute difference between the means of *MAPE* for the original and replicated models.

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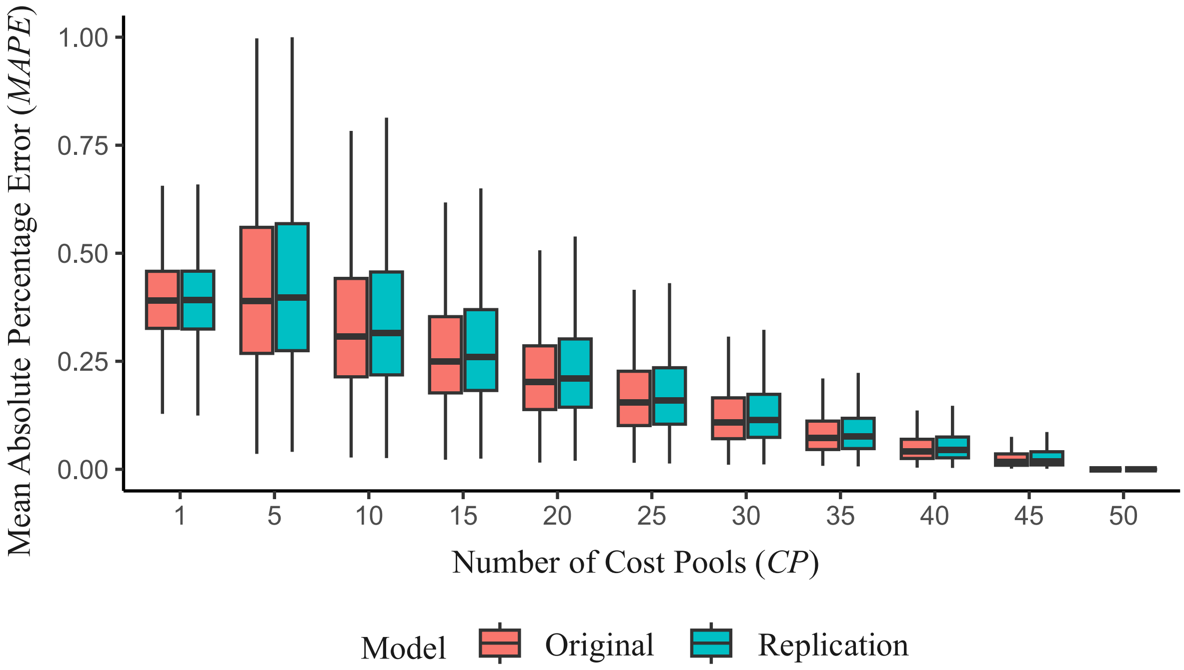
[47] See Chapter 3.1 for a more detailed description of the pattern.

Figure 16. Cost pool relationship - Replication results



Note. CP = Number of cost pools; MAPE = Mean absolute percentage error.

Table 14. Cost pool relationship – Comparison of moments of the distribution

	REPLICATION				ORIGINAL				
CP	M	SD	Skew-ness	Kurtosis	M	SD	Skew-ness	Kurtosis	|Δ| M
1	0.390	0.100	1.54	3.16	0.390	0.099	1.68	3.15	0.000
5	0.462	0.240	1.35	5.07	0.451	0.236	1.04	4.01	0.011
10	0.363	0.196	1.48	5.97	0.352	0.189	1.27	5.09	0.011
15	0.293	0.156	1.49	6.61	0.281	0.149	1.37	5.94	0.012
20	0.235	0.127	1.38	6.40	0.224	0.121	1.37	6.34	0.011
25	0.181	0.104	1.33	5.89	0.174	0.099	1.34	6.11	0.007
30	0.134	0.085	1.47	6.06	0.128	0.080	1.53	6.45	0.006
35	0.093	0.062	1.80	7.24	0.088	0.063	1.85	7.64	0.005
40	0.059	0.049	2.14	9.35	0.055	0.046	2.15	9.32	0.004
45	0.031	0.036	4.10	34.23	0.027	0.030	3.26	21.73	0.004
50	-	-	-	-	-	-	-	-	-
Overall	0.204	0.195	1.4	5.92	0.197	0.191	1.43	5.82	0.007

Note. CP = Number of cost pools; M = Arithmetic mean of *MAPE*, SD = Standard deviation of *MAPE*, |Δ| M = Absolute difference between the means of REPLICATION and ORIGINAL.

Both models produce the pattern similarly. That is, the moments of the distribution of *MAPE* along the increasing numbers of cost pools only have smaller numerical differences. For instance, the absolute difference between the means is consistently below 2%. I understand that both the original and replicated models compute statistically comparable results. Additionally, both models compute the Cost Pool Relationship pattern nearly as observed in prior studies (Balakrishnan et al., 2011), with a decreasing effect on the system-level error.

5.4.2 DEGREE OF RESOURCE SHARING – RC3

The degree of resource sharing determines the similarity of cost objects based on their production processes (Balakrishnan et al., 2011). Given a higher degree of resource sharing, cost objects in the portfolio consume indirect resources more commonly (e.g., all products require marketing efforts). This decreases with a lower degree of resource sharing (e.g., in a job shop environment), impeding the allocation of costs through the costing system (Gupta, 1993; Kerremans et al., 1991).[48]

I aim to reproduce the Degree of Resource Sharing pattern by measuring the *MAPE* for each level of *DENS* (i.e., Low, Mid, High) and combine this with three numbers of cost pools (i.e., 1, 20, 40) to check its robustness over different numbers of cost pools. Figure 17 illustrates that both models produce similar results, as corroborated by the measures of the moments of the distribution of *MAPE* for each design point in Table 15.

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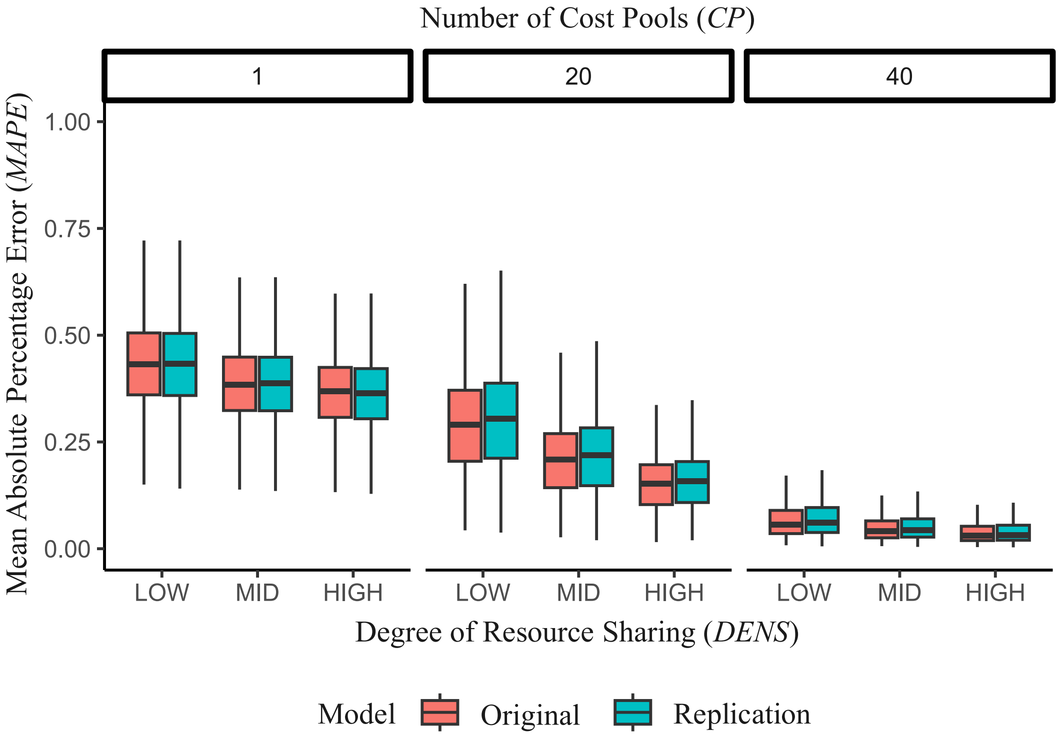
[48] See Chapter 3.2 for a more detailed description of the pattern.

Figure 17. Degree of resource sharing - Replication results



Note. *DENS* = Degree of resource sharing; *MAPE* = Mean absolute percentage error; Illustration of *MAPE* over varying degrees of *DENS* and for 1, 20, and 40 cost pools (*CP*), respectively.

Table 15. Degree of resource sharing – Comparison of the moments of distribution

		REPLICATION				ORIGINAL				
CP	**DENS**	**M**	**SD**	**Skewness**	**Kurtosis**	**M**	**SD**	**Skewness**	**Kurtosis**	**|Δ| M**
1	LOW	0.430	0.100	0.06	3.04	0.430	0.100	0.06	2.97	0.000
	MID	0.384	0.090	-0.08	2.92	0.385	0.090	0.00	2.76	0.001
	HIGH	0.364	0.080	-0.02	2.86	0.365	0.086	-0.11	2.96	0.001
20	LOW	0.306	0.130	1.13	5.63	0.301	0.134	1.14	5.59	0.005
	MID	0.220	0.100	1.23	6.22	0.217	0.100	1.21	5.89	0.003
	HIGH	0.160	0.070	1.19	5.98	0.150	0.070	1.15	5.74	0.010
40	LOW	0.070	0.050	1.87	7.45	0.070	0.050	1.87	7.19	0.000
	MID	0.050	0.040	2.12	9.08	0.050	0.040	2.06	8.87	0.000
	HIGH	0.040	0.030	2.30	11.42	0.040	0.030	2.29	11.16	0.000

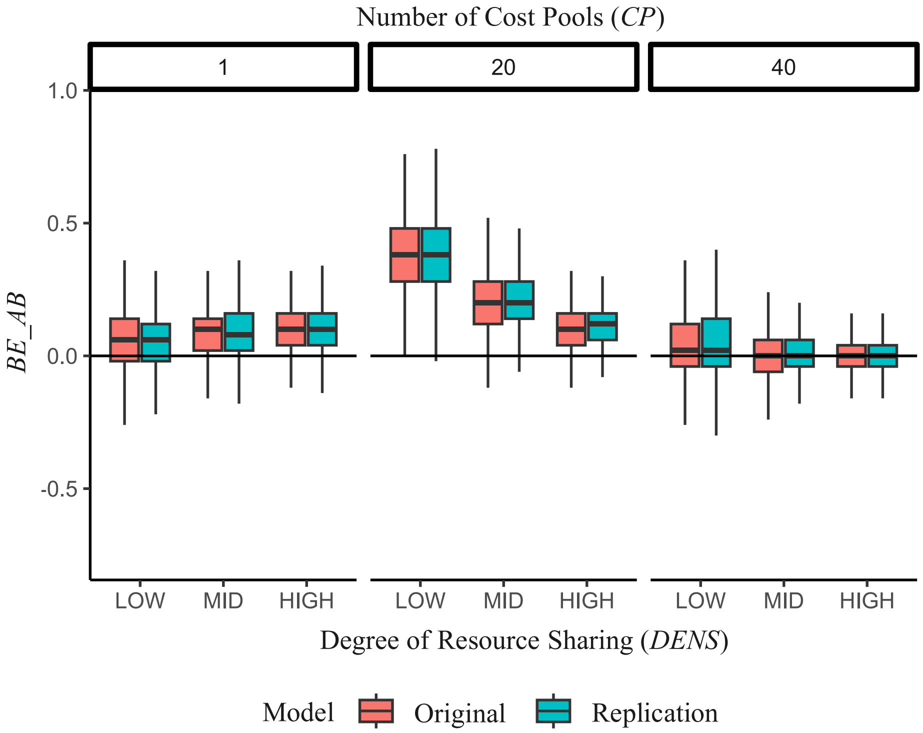
Note. *CP* = Number of cost pools; *DENS* = Degree of resource sharing.; M = Arithmetic mean of *MAPE*, SD = Standard deviation of *MAPE*, |Δ| M = Absolute difference between the means of REPLICATION and ORIGINAL.

The absolute difference between the means for each design point is equal to or less than 1%. Overall, both models reproduce the Degree of Resource Sharing pattern as described by prior studies (see Table 4).

5.4.3 DOMINANT UNDERCOSTING – CSB3

Prior empirical research and numerical experiments observe that most products are slightly undercosted, while only a few products are largely overcosted (Gupta, 1993; Labro & Vanhoucke, 2007).[49] Compared to the first two patterns at the system-level error, the Dominant Undercosting pattern focuses on the product-level error in product cost information. I follow Labro and Vanhoucke (2007) and measure the share of products that are materially undercosted or overcosted and subtract the latter from the former, to construct the measure *BE_AB*. If *BE_AB* exceeds zero, most products are materially undercosted, and the model reproduces the pattern. *BE_AB* neglects costing errors within the materiality threshold of ± 5% (Kaplan & Atkinson, 1998). The results of the numerical experiment show that, on average, *BE_AB* is larger than zero (see Figure 18), although there are a few outliers where *BE_AB* is below zero. More importantly, the results again show that both models compute near-similar results for *BE_AB* at each design point, which are supported by the moments of the distribution of *BE_AB* in Table 16.

Figure 18. Dominant undercosting – Replication results



Note. DENS = Degree of Resource Sharing; *BE_AB* = Difference between share of materially undercosted products and materially overcosted products; Illustration of *BE_AB* over varying degrees of *DENS* and 1, 20, and 40 cost pools (*CP*), respectively.

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[49] See Chapter 3.3 for a more detailed description of the pattern.

Table 16. Dominant undercosting – Comparison of the moments of distribution.

		REPLICATION				ORIGINAL				
CP	**DENS**	**M**	**SD**	**Skewness**	**Kurtosis**	**M**	**SD**	**Skewness**	**Kurtosis**	**|Δ| M**
1	LOW	0.04	0.12	-0.82	4.4	0.05	0.11	-0.93	4.8	0.010
	MID	0.08	0.09	-0.22	3.4	0.086	0.09	-0.35	3.5	0.006
	HIGH	0.09	0.08	0.004	2.9	0.096	0.08	0.006	3.09	0.006
20	LOW	0.371	0.15	-0.389	3.78	0.371	0.16	-0.34	3.58	0.000
	MID	0.2	0.11	-0.212	3.41	0.19	0.11	-0.11	3.19	0.010
	HIGH	0.11	0.08	-0.01	3.2	0.104	0.08	-0.03	3.06	0.006
40	LOW	0.05	0.15	0.92	4.6	0.05	0.14	0.96	4.56	0.000
	MID	0.014	0.1	1.1	4.9	0.014	0.1	1.1	4.88	0.000
	HIGH	0.007	0.07	0.78	4.05	0.007	0.07	0.77	4.13	0.000

Note. CP = Number of cost pools; *DENS* = Degree of resource sharing; M = Arithmetic mean of *MAPE,* SD = Standard deviation of *MAPE*, |Δ| M = Absolute difference between the means of REPLICATION and ORIGINAL.

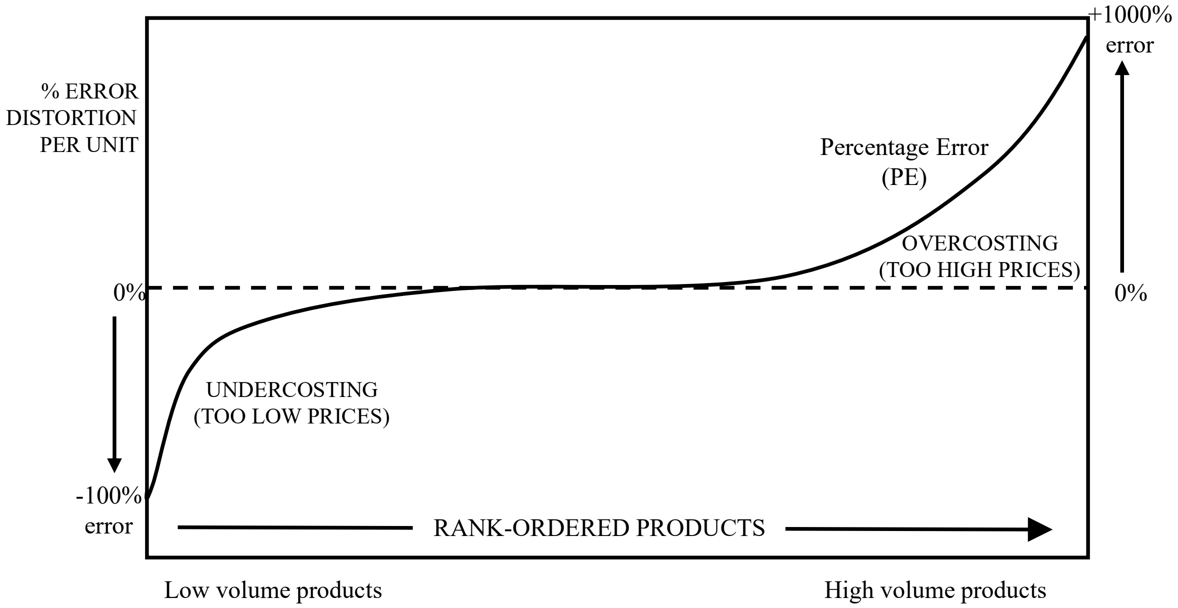
Overall, it can be concluded that both models behave similarly for all three investigated patterns. More specifically, the replicated model achieved distributional equivalence to the original model. Hence, in addition to relational equivalence (see Table 13), the replication can be considered successful in terms of distributional equivalence.

5.5 INVESTIGATING THE MECHANISM OF PRODUCT COST CROSS-SUBSIDIZATION

5.5.1 TEST OF REPRODUCIBILITY IN THE UNCHANGED COMPUTATIONAL MODEL

As the second objective of this chapter, I investigate whether the replicated model can reproduce the VBC Volume-bias pattern of product cost cross-subsidization (hereafter the pattern) and examine the required mechanism that ensures the occurrence of this pattern. The pattern shows that, in VBC systems, high-volume products are overcosted while low-volume products are undercosted. Because of the lesser effort required and costs of implementing ABC systems, organizations still use VBC systems (e.g., single cost driver costing system is employed by 30% of UK firms, based on a survey from Al-Omiri and Drury (2007)), wherefore pattern is still likely in many organizations. The pattern is often depicted as an S-curve of error when sorting cost objects along their production volumes (see Figure 19. S-Curve of the VBC volume-bias in product cost cross-subsidization) (Cokins, 2002). Consequently, this pattern negatively affects profits – assuming cost-based pricing – as the demand for the too-expensive products decreases while the demand for the too-cheap products increases (Shank & Govindarajan, 1988).

Figure 19. S-Curve of the VBC volume-bias in product cost cross-subsidization



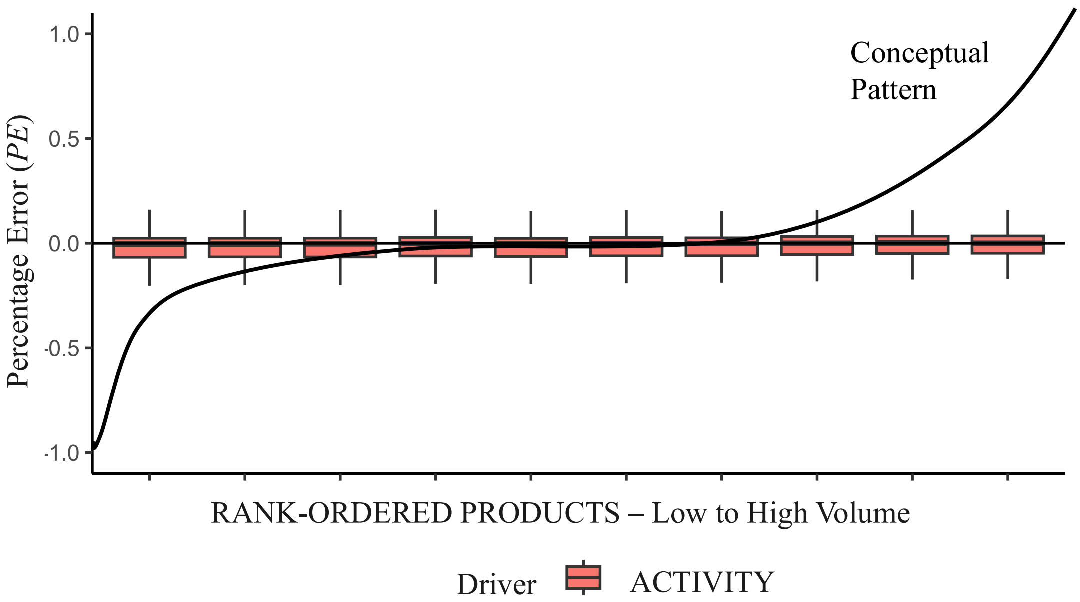
According to Cooper and Kaplan (1988b), the pattern occurs when the employed cost driver inaccurately reflects true resource consumption by focusing only on unit-level resource consumption (or production volumes). More specifically, such cost drivers do not capture resource consumption decoupled from production volumes. For example, imagine two people having dinner at a restaurant. Person A orders two main dishes, while Person B orders only one. They also decide to share a bottle of wine that costs $30. Person A drinks about one-third of the bottle, while Person B drinks two-thirds. The number of dishes reflects the unit-level resource consumption, while the wine consumption is the non-unit-level resource usage. Note that the wine consumption is decoupled from the number of dishes ordered and even negatively correlates. A volume-based cost driver might allocate costs for the bottle of wine based on the number of dishes ordered (i.e., unit-level consumption). Consequently, two-thirds of the wine cost ($20) is allocated to Person A and one-third ($10) to Person B because Person A orders two main dishes, while Person B orders only one. Thus, Person A is overcosted (20>10), and Person B is undercosted ($10 < 20$). The volume-based cost driver thus neglects non-unit-level resource consumption (i.e., the amount of wine consumed), and the pattern emerges. A solution would be to refine the costing system and to allocate additional costs based on the resource consumption at the other tiers of the cost hierarchy (in manufacturing firms, batch-level, product-sustaining-level, or facility-sustaining-level). In other words, additional cost drivers that measure non-unit-level resource consumption are required (e.g., the number of glasses of wine consumed).

This discussion suggests two relevant components to ensure the emergence of a product cost cross-subsidization pattern. First, some proportions of overall costs must be decoupled from production volume, meaning they have a zero or negative correlation to volume (or unit-level consumption). These are termed non-unit-level costs, while those strongly linked to volumes are termed unit-level costs. Hence, in the first step, I simplify the four-tier cost hierarchy (see Chapter 2.3) by converting it into these two segments and argue that non-unit-level costs are necessary for the pattern to emerge.

Second, the example also illustrates that it is required that the cost driver of the employed costing system allocates costs based on volumes. A cost driver that additionally considers non-unit-level resource consumption will diminish the pattern (Noreen, 1991). More generally, a refined costing system employing cost drivers that allocate costs based on resource consumption, which reflects all present levels in the firm's cost hierarchy, should prevent the occurrence of the pattern (Anderson & Sedatole, 2013). This conception led to the development of ABC, where the cost drivers in the costing system ideally measure resource consumption on all tiers of the cost hierarchy(Cooper & Kaplan, 1991). Case studies on firms observe that ABC shifts reported costs of high-volume products downward and costs of low-volume products upward (Duh et al., 2009; Tai et al., 2015), indicating the reduction of the product cost cross-subsidization pattern. Still, the pattern and its mechanism remain uninvestigated in settings that exceed the limit of numerical examples or single cases.

For the replicated model, it can be expected that the pattern of product cost cross-subsidization will not emerge because (1) the model currently only computes resource consumption that is highly correlated with production volume and further employs an activity-based cost driver that would consider non-unit-level resource consumption (Balakrishnan et al., 2011). To test this assumption, I recreate the S-Curve in Figure 19’s conceptual illustration with the data generated by the replicated model. For each run, I group all products into deciles based on their production volumes and calculate the percentage error *PE* for each product. According to the pattern, the lowest-volume (highest-volume) deciles should have a negative (positive) percentage error. Figure 20 shows that, for the replicated model, there is no systematic distortion along the rank-ordered products, suggesting that the pattern cannot be reproduced.

Figure 20. Product cost cross-subsidization pattern in the replicated model



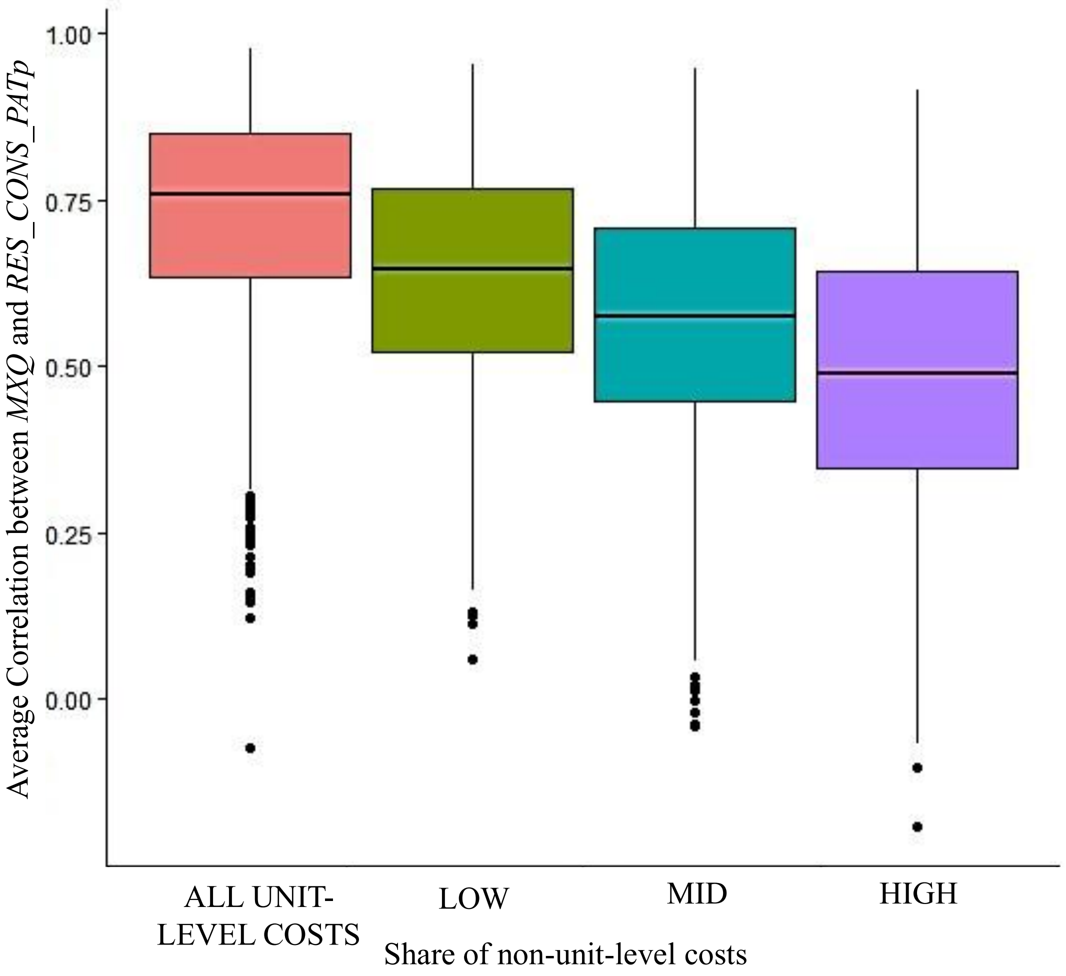
Note. *PE* = Percentage error; *ACTIVITY* = Activity-based cost driver selection heuristic (*BIGPOOL*).

5.5.2 EXTENSION OF THE COMPUTATIONAL MODEL TO REPRODUCE THE PATTERN

To reproduce the pattern, I implement the two components as suggested: the volume-based cost driver and non-unit-level costs. First, I employ production volumes (i.e., *MXQ*) as the allocation base for a product's overall resource consumption to construct a volume-based cost driver. Other cost drivers, such as direct labor and machine hours, exist for volume-based costing systems, which are also related to production volumes or production-linked activities (Shank & Govindarajan, 1988) and should compute similar results. However, production volumes are employed as the only type of volume-based cost driver to reduce the complexity of this modeling approach. An exploratory analysis conducted in Mertens and Meyer (2016) indicates high similarity between different volume-based drivers and further justifies this approach.

Second, I split the resource consumption matrix (*RES_CONS_PAT*) into unit-level and non-unit-level resources (the columns in the matrix) to model non-unit-level costs. As in the original model, the unit-level resource consumptions are multiplied by the production volumes. This results in highly correlated resource consumption with production volumes, defined as unit-level consumptions. Figure 21 illustrates that when all resources are multiplied by production volumes, the median correlation between resource consumption (*RES_CONS_PATp*) and production volumes (*MXQ*) is above 0.75. This correlation decreases with an increased share of non-unit-level costs, showing that the non-unit-level costs in the model correlate less with *MXQ*.

Figure 21. Correlation between production volumes and resource consumption



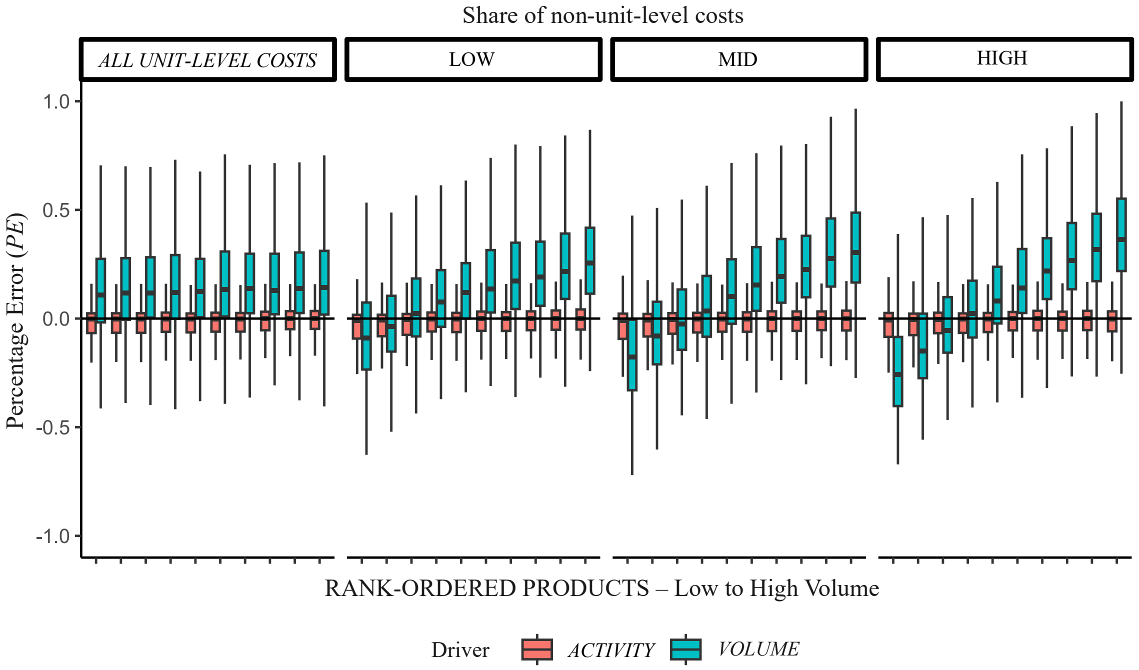
Note. LOW = Share of costs that are consumed on the non-unit-level = 20% - 33%; MID = Share of costs that are consumed on the non-unit-level = 34% - 46%; HIGH = Share of costs that are consumed on the non-unit-level = 46%-60%.

Based on the empirical observations in Table 3 that roughly 40% of activities are *not* on the unit-level, I randomly set 20% to 60% of all resources and costs to the non-unit level. Additionally, for this experiment, I divide this simple cost hierarchy into four specifications, depending on the share of non-unit-level resources – (1) all resources are on the unit-level and their consumption correlates with production volumes (as in the original model), (2) 20%-33% of all resources are non-unit-level (LOW), (3) 34%-46% of all resources are non-unit-level (MID), and (4) 47%-60% of all resources are non-unit-level (HIGH). I control all possible costing system designs and production environment parameters (as in the replication experiment in Table 12).

Figure 22 illustrates the results for the different settings of the numerical experiment with the four specifications of the simple cost hierarchy and the two types of cost drivers (*VOLUME* and *ACTIVITY*). As suspected, a volume-based cost driver *and* non-unit-level costs are required to produce the pattern. More precisely, in these treatments, low-volume products are likely undercosted, and high-volume products are likely overcosted, as described by the pattern. Additionally, a greater share of non-unit-level resources strengthens the pattern, as shown in Figure 22. This substantiates that the expected mechanism is driving the pattern and that the simple cost hierarchy containing two types of resource consumption (i.e., the two tiers: unit-level and non-unit-level) is sufficient to reproduce the pattern. On a different note, these results highlight that ABC systems are unaffected by non-unit-level resource consumption regarding the VBC Volume-bias and overall accuracy of reported product costs. That is, Figure 22 illustrates a similar percentage error *PE* for all products in the portfolio. Moreover, *PE* is close to zero in all settings (i.e., the size of the boxplots is small), indicating a low overall error in reported product costs. This result underscores the superiority claims of ABC advocates (Cooper & Kaplan, 1999).

To quantify the pattern, I compute the variable *VB_PATTERN*. *VB_PATTERN* is the difference between the percentage error *PE* for the products in the two highest and two lowest production volume deciles. In other words, I calculate the difference between the two extreme right-hand boxes and the two extreme left-hand boxes in the boxplots of Figure 22. Hence, the greater the value for *VB_PATTERN*, the greater the difference between the two groups, and the greater the strength of the pattern (i.e., the steeper the S-Curve). I observe that in VBC systems, *VB_PATTERN* increases as the share of non-unit-level resources increases.

Figure 22. Product cost cross-subsidization pattern for VBC and ABC



Note. LOW = Share of costs that are consumed on the non-unit-level = 20% - 33%; MID = Share of costs that are consumed on the non-unit-level = 34% - 46%; HIGH = Share of costs that are consumed on the non-unit-level = 46% -60%. For the volume-based driver, the mean values for VB_PATTERN in the three types of cost hierarchies are: ALL UNIT-LEVEL COSTS = 0.03; LOW = 0.31; MID = 0.45; HIGH = 0.58.

Case studies that observe the pattern empirically also report usage of volume-based cost drivers (Duh et al., 2009; Rezaie et al., 2008; Tai et al., 2015), which is in line with the suggested mechanism. Empirical research is still inconclusive about the existence of cost hierarchies (Anderson & Sedatole, 2013). Since non-unit-level resource consumption is required for the emergence of the pattern – according to the identified mechanism – it can be argued that this hints at the existence of at least two tiers in the cost hierarchy (e.g., unit-level and batch-level) in empirical production environments.

As an additional analysis, I conduct a regression analysis to measure the effects of other variables on the variable *VB_PATTERN*. Table 17 depicts the direct and interaction effects of the input variables on *VB_PATTERN* in an effect matrix (Lorscheid et al., 2012). The binary variable *VolumeDriver* indicates whether the employed cost driver is based on production volumes (*VolumeDriver* = 1) or activities (*VolumeDriver* = 0, *BIGPOOL*, see Table 12). The variable *non_unit_size* provides the share of resources (i.e., columns in *RES_CONS_PAT*) that is *not* multiplied with production quantities and hence are non-unit level resources (20% - 60%).

Table 17. Effect matrix for *VB_PATTERN*

	Factors								
Factors	*CP*	*DISP1*	*DISP2*	*DENS*	*COR1*	*COR2*	*Q_VAR*	*Volume Driver*	*non_unit _size*
CP	-0.02**	0.00	0.00	0.00	0.00	0.00	-0.01**	0.02**	0.00
DISP1		0.00	-0.01**	-0.01**	0.00	0.00	0.00	-0.01**	-0.01**
DISP2			0.01**	-0.01**	0.00	0.00	0.00	0.04**	0.03**
DENS				-0.05*	-0.01**	-0.01**	0.00	-0.04**	0.01**
COR1					0.01**	0.00	0.00	0.01**	0.00
COR2						0.01**	0.00	0.01**	-0.01**
Q_VAR							0.12**	0.11**	0.12**
Volume Driver								0.38**	0.36**
non_unit _size									0.37**

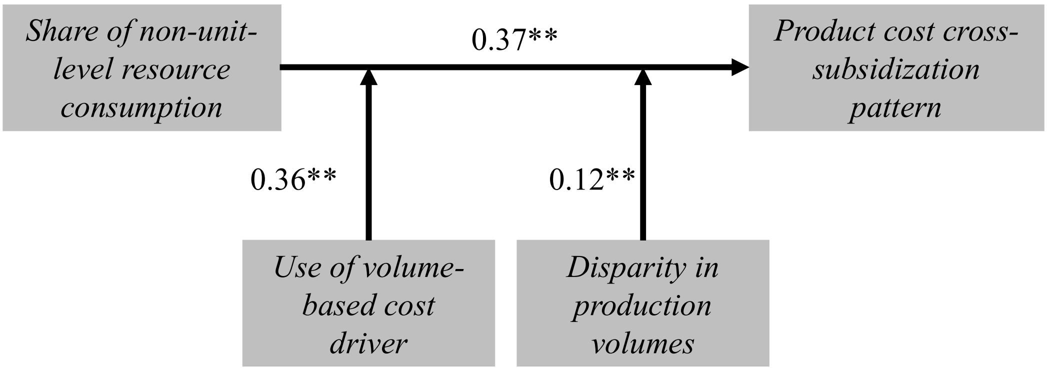
R^2 = .457**
N = 316,800

Note. Dependent variable: *VB_PATTERN*; *CP* = Number of cost pools*;* *DISP1* = Number of “big” resources; *DISP2* = Share of costs that are assigned to “big” resources; *DENS* = Degree of resource sharing; *COR1*= Correlation between volume resources; *COR2* = Correlation between batch resources; *Q_VAR* = Disparity in production volumes; *VolumeDriver* = Indicator variable for the usage of volume-based cost driver (1) or activity-based cost driver (0); *non_unit_size* = share of resources that are non-unit-level; Presented β coefficients are standardized; * indicates p < .05. ** indicates p < .01.

The presence of a volume-based cost driver (*VolumeDriver*) and an increase in non-unit-level costs (*non_unit_size*) have the strongest effect on the emergence and strength of the pattern (0.38** and 0.37**, respectively). In addition, the interaction effect between these two variables is substantial (0.36**), which indicates the importance of the interplay of the two model components to produce the pattern. Moreover, Table 17 reports that the disparity in production volumes within the product portfolio, measured by *Q_VAR*, exerts a strong positive effect on *VB_PATTERN*. This also aligns with the explanation of the pattern's mechanism. A higher disparity in production volumes results in a volume-based cost driver that more strongly overstates (understates) the non-unit-level resource consumption of high-volume (low-volume) products. For instance, returning to the restaurant example, this means that Person A would eat four dishes while Person B would eat only one. Consequently, products with extremely high or extremely low production volumes are profoundly more affected by cross-subsidization when a volume-based cost driver is used.

To summarize the results, it is now possible to depict the mechanism behind the VBC Volume-bias pattern of product cost cross-subsidization. Figure 23 shows the main effect of the share of non-unit-level resource consumption on the pattern (*VB_PATTERN*) and the moderating effects of using a volume-based cost driver and disparity in production volumes.

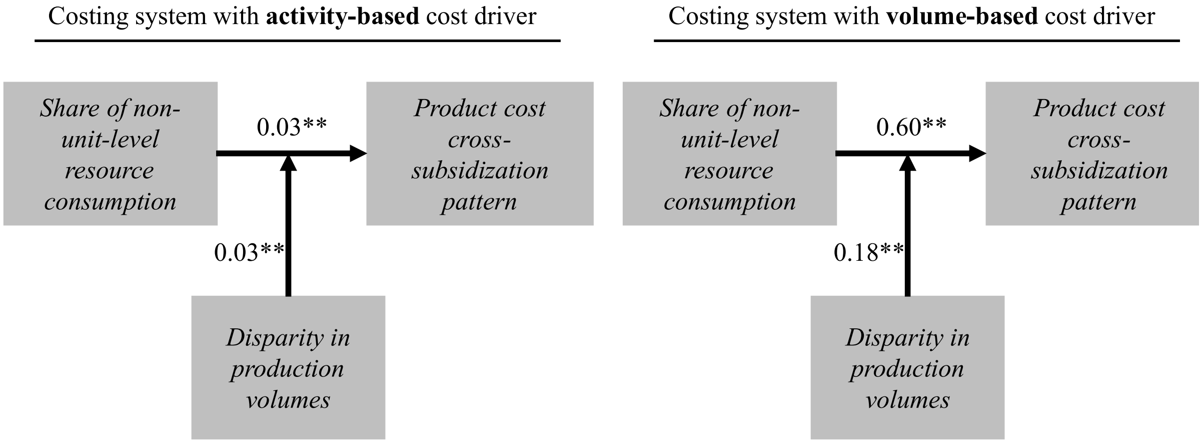
Figure 23. Mechanism of the product cost cross-subsidization pattern



Note. The product cost cross-subsidization pattern is measured using the variable *VB_PATTERN*; *Q_VAR* measures disparity in production volumes; Use of volume-based cost driver is the indicator variable for usage of volume-based cost driver (1) or activity-based cost driver (0); Share of non-unit-level resource consumption is measured using the variable *non_unit_size*; Presented β coefficients are standardized; * indicates p < .05. ** indicates p < .01; N = 315,600.

A split of the sample into costing systems with and without volume-based drivers (see Figure 24) shows that a strong relationship between the share of non-unit-level resource consumption and the pattern of product cost cross-subsidization (0.60** vs 0.03**) is only apparent in VBC systems. Similarly, the interaction effect of the disparity of production volumes is much stronger in VBC systems (0.18** vs 0.03**). This analysis further corroborates the identified mechanism.

Figure 24. Sample split for additional analysis of the mechanism behind the VBC volume-bias pattern


Costing system with **activity-based** cost driver

Costing system with **volume-based** cost driver

Note. The product cost cross-subsidization pattern is measured using the variable *VB_PATTERN*; *Q_VAR* measures disparity in production volumes; Share of non-unit-level resource consumption is measured using the variable *non_unit_size*; Presented β coefficients are standardized; * indicates p < .05. ** indicates p < .01; N = 158,400 for each model.

5.5.3 EXTENSION OF THE COMPUTATIONAL MODEL BY AN ABC COST HIERARCHY

Although the implementation of non-unit-level costs that do not vary with production quantities suffices as a simple cost hierarchy to reproduce and explain the mechanism behind the pattern of product cost cross-subsidization, it does not represent a full four-tier ABC cost hierarchy as theoretically proposed (Cooper & Kaplan, 1991). A full ABC cost hierarchy distinguishes between unit-level, batch-level, product-sustaining-level, and facility-sustaining-level costs. The current modeling approach models resource consumption that varies with production volumes (unit-level) and non-unit-level consumption that varies randomly. The following experiment investigates whether a further separation of non-unit-level costs into batch-level, product-sustaining-level, and facility-sustaining-level costs affects the emergence and strength of the product cost cross-subsidization pattern. Based on empirically observed and theoretically expected structures of the ABC cost hierarchy from Chapter 2.3, I implement the ABC cost hierarchy in the model as follows. For this, I generally distinguish between an implementation based on the theoretically expected and an empirically observed implementation (upper and lower diagonal relations in Table 2). I define the following modeling approaches for these two implementation approaches into the resource consumption matrix (RES_CONS_PAT).[50]

First, I continue modeling unit-level costs as in the original model and the model with the *simple cost hierarchy* in the previous experiment by multiplying randomly drawn resource consumption λ with production volumes q to generate highly correlated unit-level costs y. Second, to model batch-level resource consumption for the *theoretical* ABC cost hierarchy, I divide the randomly drawn normal distributed resource consumption λ for each batch-level resource and product by the production quantities q of the respective product. Hence, greater production quantities result in larger batch sizes and decreased batch-level costs y per produced unit (i.e., negative correlation). To reflect the *empirical* ABC cost hierarchy, I model a weak positive correlation between unit-level and batch-level resource consumption by multiplying the random resource consumption λ with the respective production quantities q and a random number f drawn from a normal distribution with mean = 1 and standard deviation = 0.25.

Next, the product-sustaining-level resource consumption is modeled by multiplying the product of random resource consumption λ and production quantities q with the factor r drawn from a normal distribution with mean = 1 and standard deviation = 0.25. The random value r can be seen as the type of manufacturing technology that either couples or decouples product-

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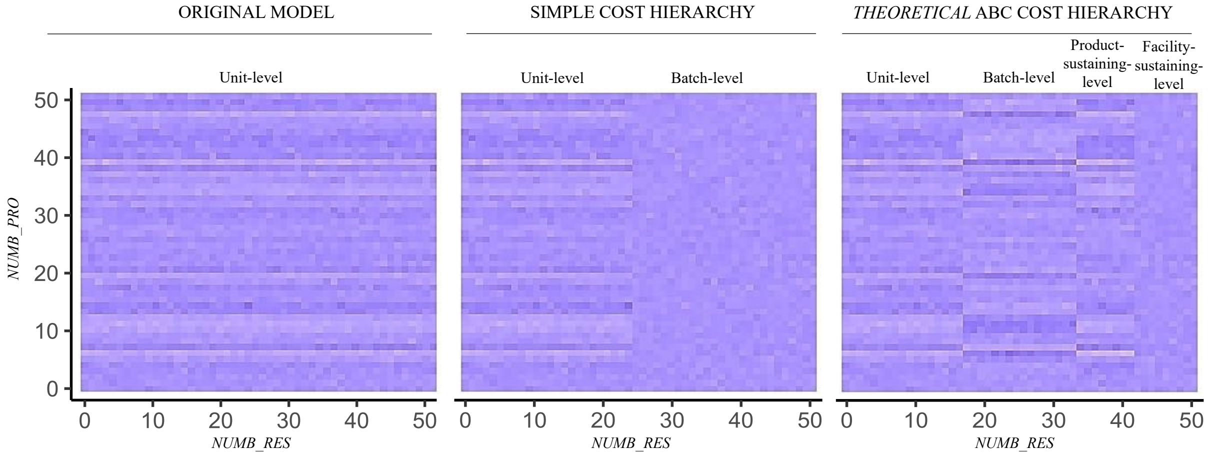
[50] Due to the modeling differences between the model from Balakrishnan et al. (2011) (Chapter 4) and the ABL framework, different modeling approaches are required to implement an ABC cost hierarchy.

sustaining activities from unit-level activities (e.g., Advanced Manufacturing Technology vs. Workshop Production) (Anderson & Sedatole, 2013) and thus decreases or increases its linkage and correlation. Moreover, in the *theoretical* setting, a positive correlation between unit-level and product-sustaining-level resource consumption results in a negative correlation between batch-level and product-sustaining-level resource consumption, as posited by Ittner et al. (1997). Overall, there is no distinction for product-sustaining-level resource consumption between the *theoretical* and *empirical* modeling approach, as observations and theoretical predictions align.

Finally, in the *simple cost hierarchy* (prior section), I generated the facility-level costs y for each product and respective resource solely from a random resource consumption λ. This resulted in resource consumption with no significant correlation between facility-level resource consumption and other tiers of the ABC cost hierarchy. This reflects the theoretical intuition concerning facility-level costs (Cooper & Kaplan, 1991). However, empirical accounting research also reports strong positive (and some negative) correlations between facility-level costs and all other tiers of the ABC cost hierarchy. Hence, to relax the strict decoupling from other tiers of the ABC hierarchy, I multiply the randomly drawn resource consumption λ for the facility-level resources with one of the respective weighting factors (i.e., q, r, or f) of the other tiers. I randomly select with which factor λ is multiplied to provide a basis for all possible scenarios. Figure 25 exemplarily illustrates how the resource consumption matrix (*RES_CONS_PAT*) contains different tiers of resource consumption when the *simple cost hierarchy* or the *theoretical* ABC cost hierarchy is introduced, compared to the original model. Resource consumption is less homogeneous among all resources because it does not solely correlate with production quantities.

Figure 25. Exemplary visualization of resource consumption patterns with different types of cost hierarchies



Note. Each row in the matrix reflects the relative resource consumption of the respective product. Each column in the matrix reflects how one resource is consumed by all products (rows). *NUMB_PRO* = Number of products in the firm's portfolio (50). *NUMB_RES* = Number of resources consumed (50).

Table 3 reports that 54% are associated with unit-level costs, 10.25% are batch-level costs, 15.80% are product-sustaining costs, and 15.30% are facility-sustaining costs. Based on these observations, I randomly model the following percentages of costs for each tier to add up to 100% in total: unit-level = 40% – 70%, batch-level = 10% – 32%, product-sustaining-level = 10% – 24%, and facility-sustaining-level = 5% – 15%. Table 18 reports the Pearson correlations for resource consumption between the different tiers of the four modeled cost hierarchies. Overall, the approach to model a variety of cost hierarchies aims to cover different industry settings, strategic orientations, and production technologies to increase the generality of the results. For instance, Advanced Manufacturing Technologies (AMT) can shift resource consumption from batch-level and product-sustaining-level toward unit-level or facility-sustaining-level (Anderson & Sedatole, 2013). Supply chain design (i.e., distance to supplier or sales markets) may determine logistics efforts, thus increasing batch-level costs (Anderson & Dekker, 2009). A firm's strategic orientation affects research and development efforts (Banker et al., 2021a) or product design (Anderson & Sedatole, 1999) and may shift costs toward facility-sustaining- or product-sustaining-level costs. Anderson and Dekker (2009) and Banker et al. (2018) review prior findings on how such factors influence costs and resource consumption.[51]

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[51] See Chapter 2.3 for the review on cost hierarchies and resource consumption in this thesis.

Table 18. Pearson correlations (and standard deviations in brackets) for the resource consumptions between the different tiers of the implemented cost hierarchies

Tier	Modeling	Unit-level	Batch-level	Product-sustaining-level	Facility-sustaining-level
		ORIGINAL MODEL			
Unit	$y = \lambda q$	1			
Batch	$y = \lambda q$	.46[1]	1		
		[0.22]			
Product-sustaining	-	-	-	1	
Facility-sustaining	-	-	-	-	1
		SIMPLE COST HIERARCHY			
Unit	$y = \lambda q$	1			
Batch	-	-	1		
Product-sustaining	-	-	-	1	
Facility-sustaining	$y = \lambda$	.15[2]	-	-	1
		[0.22]			
		THEORETICAL ABC COST HIERARCHY			
Unit	$y = \lambda q$	1		-	-
Batch	$y = \lambda / q$	-.53	1		
		[0.23]			
Product-sustaining	$y = \lambda q r$	.43	-.38	1	-
		[0.23]	[0.21]		
Facility-sustaining	$y = \lambda$	.00	.00	.00	1
		[0.15]	[0.14]	[0.13]	
		EMPIRICAL ABC COST HIERARCHY			
Unit	$y = \lambda q$	1		-	
Batch	$y = \lambda q f$	.44	1		
		[0.21]			
Product-sustaining	$y = \lambda q r$	.42	.32	1	-
		[0.19]	[0.17]		
Facility-sustaining	$y = \lambda[q][r][f]$	.00	.09	.09	1
		[0.14]	[0.20]	[0.23]	

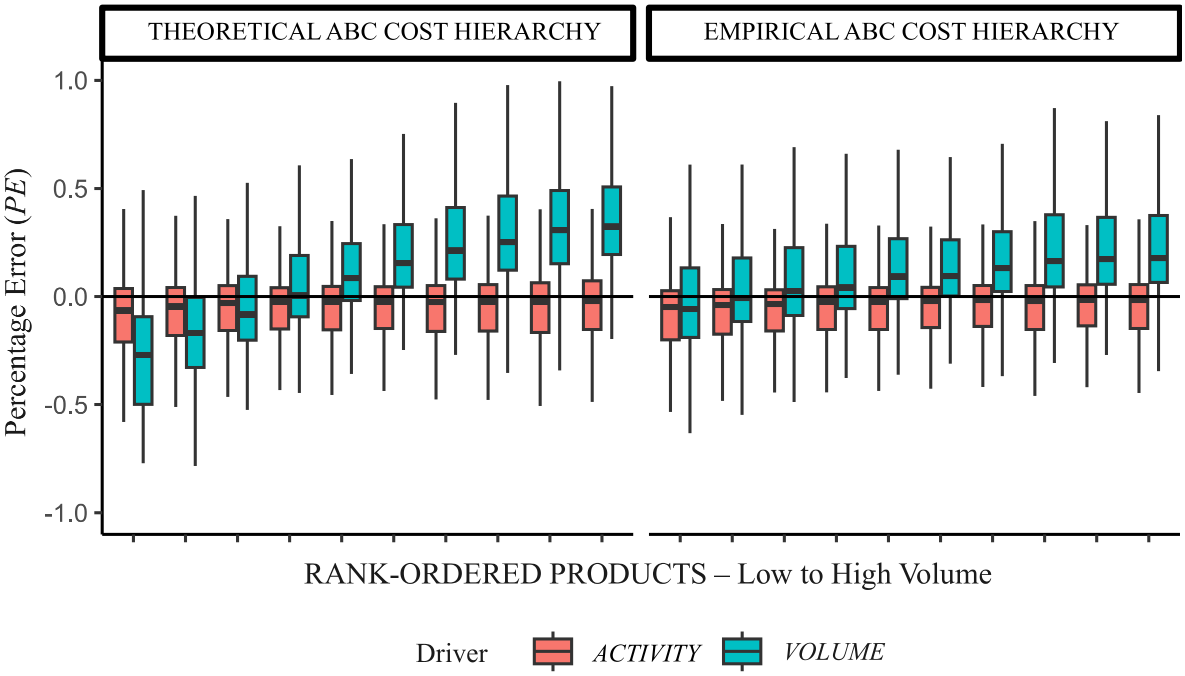
Note. All correlations are significant with $p < 0.01$. N = 240,000 observations. Standard deviations are reported in square brackets. y = cost consumption; λ = random resource consumption drawn from a normal distribution with mean = 1 and standard deviation = 0.25; r = normal distribution with mean = 1 and standard deviation = 0.25; f = normal distribution with mean = 1 and standard deviation = 0.25.

[1] Note that in the original model, Anand et al. (2019) generate one section of the resource consumption matrix to reflect batch-level resources by employing the input variables *COR1* and *COR2*. However, all resource consumptions λ are multiplied by production quantities.

[2] In the simple cost hierarchy modeled in the previous section, the non-unit-level costs are modeled without linkage to production quantities, wherefore I classify them here as facility-level costs.

Based on the logic that underlies the ABC cost hierarchy, negative correlations should be a stronger driver for the pattern than no correlations because the strong negative correlations resemble anti-proportional resource consumptions that contradict the costs reported by employed cost drivers (Noreen, 1991), as in the restaurant example. Hence, I assume that the *theoretical* ABC cost hierarchy results in the strongest product cost cross-subsidization. The results of the third simulation experiment support this assumption. Figure 26 illustrates the product cost cross-subsidization pattern for firms with *theoretical* and *empirical* ABC cost hierarchies. The pattern does not emerge as pronounced in empirical ABC cost hierarchies, although there is a small overcosting bias toward high-volume products. However, as expected, the cross-subsidization is strongest in the *theoretical* ABC cost hierarchy.

Figure 26. Product cost cross-subsidization pattern in the theoretical and empirical ABC cost hierarchy



Note. *PE* = Percentage Error between reported product costs (*PCH*) and true benchmark product costs (*PCB*). For the volume-based driver, the mean values for *VB_PATTERN* in the two ABC cost hierarchies are: theoretical = 0.40; empirical = 0.14.

This strengthens the argument and theoretical predictions (Hwang et al., 1993) that the correlations between the different tiers' resource consumption are critical for the pattern to emerge. Consequently, as the *empirical* ABC cost hierarchy contains relatively high positive correlations, the cross-subsidization is weak, whereas in the *theoretical* ABC cost hierarchy, resource consumption can be negatively correlated, and the cross-subsidization is strongest. This may hint at a divergence between theoretically expected and empirically observed cost hierarchies and corresponding cross-subsidization in product costs. Despite this, I argue that it is empirically difficult to attain correlations between two or more tiers in a firm's resource consumption. A reason is that the true resource consumption pattern is not empirically measurable (Labro, 2006a). Researchers must rely on employed cost drivers that are possibly already distorted by aggregation, specification, and measurement errors (Datar & Gupta, 1994). Additionally, Cooper and Kaplan (1991) posit that when non-unit-level resource consumption is divided by unit-level cost drivers, the impression of high correlation can arise. Finally, I again employ the variable *VB_PATTERN* to quantify the drivers of the VBC Volume-bias in product cost cross-subsidization. Table 19 reports the regression results for the four different cost hierarchies.

Table 19. Regression analysis for *VB_PATTERN* in the four cost hierarchy models

Predictor	ORIGINAL MODEL	SIMPLE COST HIERARCHY	THEORETICAL ABC COST HIERARCHY	EMPIRICAL ABC COST HIERARCHY
Production Environment				
DISP1	-0.03**	-0.03**	-0.05**	-0.07**
DISP2	-0.02**	0.01**	0.12**	0.12**
COR1	-0.01**	-0.01**	0.00	0.00
COR2	0.02**	-0.01**	0.00	0.00
DENS	-0.03**	-0.01**	-0.11**	-0.10**
Q_VAR	0.05**	0.23**	0.24**	0.16**
bl_size	0.00	-	0.08**	0.02**
pl_size	-	-	0.02	0.01**
fl_size	-	0.12**	0.04**	0.10**
Costing System				
CP	-0.01**	-0.01**	0.00	-0.00
Volume Driver	0.03**	0.53**	0.56**	0.32**
R^2	.006**	.350**	.412**	.170**
Mean	0.02	0.23	0.40	0.14

Note. Dependent Variable = *VB_PATTERN*; *CP* = Number of cost pools; *DISP1* = Number of "big" resources; *DISP2* = Share of costs that are assigned to "big" resources; *DENS* = Degree of resource sharing; *COR1*= Correlation between volume resources; *COR2* = Correlation between batch resources; *Q_VAR* = Disparity in production volumes; *VolumeDriver* = Indicator variable for the usage of a volume-based cost driver (1) or activity-based cost driver (0); *bl_size* = share of resources that are batch-level; *pl_size* = share of resources that are product-sustaining-level; *fl_size* = share of resources that are facility-sustaining-level; Presented β coefficients are standardized; * indicates p < .05. ** indicates p < .01.

The R^2 is highest for the *theoretical* ABC cost hierarchy because resource consumption follows systematic rules in that setting; therefore, the resource consumption matrix (*RES_CONS_PAT*) is the most structured. Hence, it holds more information compared to a pure random matrix.

The regression models of the original model and the *empirical* ABC cost hierarchy can only explain smaller fractions of the variation of *VB_PATTERN* because resource consumption is more randomly generated (see Figure 25 as an example). Interestingly, due to structuring the resource consumption matrix into more than two tiers (i.e., for the *theoretical* and *empirical* ABC cost hierarchies), especially the parameters *DISP2* and *DENS* become more relevant for cross-subsidization. *DISP2* primarily defines the heterogeneity of resource costs. Hence, in a more structured matrix where some resource consumptions are not proportional to production quantities, heterogeneous resource costs can be a lever to increase the cross-subsidization when production quantities are employed as a cost driver. In other words, allocating costs based on production volume is especially detrimental (with high cross-subsidization) when a few non-unit-level resources contain a large share of costs. This principle also applies to *DENS.* The greater the degree of resource sharing, the more homogeneous the resource consumption along different tiers of the hierarchy, resulting in a less pronounced pattern. In summary, these results suggest that distinguishing between different levels and types of the cost hierarchy further contributes to a better understanding of the pattern.

5.6 CONCLUSION

This chapter investigates the mechanism behind the VBC Volume-bias pattern of product cost cross-subsidization (CSB1 from Table 4) in a large-scale simulation experiment based on a replication of the computational model from Anand et al. (2019). The replication follows best practices of computational replications, including building on the conceptual model underpinning the original model and detecting potential implementation and programming errors. Additionally, a pattern-oriented modeling strategy is applied to guide the more detailed analyses within the original and replicated models and their behavior (Grimm et al., 2005). Three well-documented patterns from Table 4 are selected to test the distributional and numerical equivalence of the models' outcomes. I compared the statistical moments of the distributions of interest to assess their likeness. This approach is more straightforward and robust than the traditional statistical tests used to test distributional equivalence (e.g., t-tests or Kolmogorov-Smirnov-test), which are deemed problematic considering the large sample sizes typical for simulation experiments (White et al., 2014). While numerical equivalence was not achieved (as expected for models with several stochastic components), I found distributional equivalence for all patterns. In sum, the results verified relational and distributional equivalence between the original and replicated models and confirmed replication success.

Next, the replicated model is used to investigate the mechanism behind the VBC Volume-bias pattern of product cost cross-subsidization. The original model was not designed to reproduce this pattern, and the initially implemented production environment only created unit-level costs that correlated highly with production quantities. I extended the model to reproduce the observed pattern by adding two new components: a volume-based cost driver and non-unit-level costs. The findings revealed that both components must be incorporated to reproduce the pattern successfully. This suggests that a more diverse production environment, including non-unit-level costs, is required for product cross-subsidization in volume-based costing systems. A large-scale simulation experiment allowed for analyzing the pattern's underlying mechanism in detail, identifying the key variables involved, and quantifying their relationships. The results showed that dispersed production quantities and a high share of non-unit-level costs increase the pattern's strength in volume-based costing systems. Therefore, in such settings, the managers of firms should act cautiously while making decisions based on costs.

To better differentiate the impact of non-unit-level costs, the model is extended in a second way by implementing two complete four-tier ABC cost hierarchies. This allowed to explore the impact of different cost hierarchies on the pattern of product cost cross-subsidization, thereby gaining a more detailed understanding of how the pattern emerges in different production environments. The approach to investigating the full effect of the four-tier ABC cost hierarchy on the pattern of product cost cross-subsidization is based on empirical observations and theoretical predictions. I derive a pattern-orientated modeling approach to achieve this. The results show that the pattern diminishes when batch-level, product-sustaining-level, or facility-sustaining-level resource consumption does not have a zero or negative correlation with unit-level cost drivers, corroborating the identified mechanism. While the VBC Volume-bias pattern has been observed in several case studies (Duh et al., 2009; Rezaie et al., 2008), the identified mechanism suggests that both empirical and theoretical ABC cost hierarchies can produce the pattern. However, these findings also indicate that the theoretical hierarchies with negative correlations are especially critical in generating this pattern and may exist in the production environments of certain firms for which the pattern has been reported.

This chapter makes two significant contributions to the literature. First, the results contribute to simulation-based and analytical research on costing system design and accuracy by successfully replicating the ABL framework and extending it with a volume-based cost driver and different cost hierarchies. By doing so, I complement investigations that were limited to a few examples (Hwang et al., 1993) or that focused on the product cost cross-subsidization pattern of ABC systems (Labro & Vanhoucke, 2007). This chapter also contributes to the discussion of volume-based costing (VBC), which is still widely used in practice (Al-Omiri & Drury, 2007). More specifically and in the grand scheme of this thesis, I add to the understanding and validity of current patterns and notions of errors in cost information, listed in Chapter 3, by depicting the precise mechanism of the VBC Volume-bias (CSB1).

Additionally, the developed modeling approach can be helpful when investigating decisions and practices that require more detailed cost hierarchies, such as customer or product profitability analysis. Such insights can be particularly relevant and add a new dimension to existing studies. This underscores the importance of measuring the cost hierarchy in practice when investigating cost-based decision-making. Overall, the findings contribute to the discussion on costing system design and provide valuable insights into cost accuracy and errors in reported cost information.

Second, this chapter adds to the discussion of cost hierarchies and true resource consumption in accounting research (Anderson & Sedatole, 2013). Specifically, I synthesize empirical observations with theoretical predictions about resource consumption correlation to develop a modeling approach for different cost hierarchies. By linking simulation-based research on costing system design with empirical research on ABC cost hierarchies (Ittner et al., 1997), the approach in this chapter leverages the advantages of simulation modeling to examine the conditions under which cost hierarchies are less likely to result in product cost cross-subsidization in VBC systems. This information can be valuable when estimating the potential occurrence of cross-subsidization in product costs in practice. In addition, this research offers a novel perspective on cost driver research (Banker & Johnston, 2006) by investigating the emergence of the VBC volume-bias pattern of product cost cross-subsidization in both theoretical and empirical ABC cost hierarchies. I detail this understanding by linking specific types of cost hierarchies and their effect on the pattern of product cost cross-subsidization in greater detail.

Finally, this investigation comes with limitations. First and foremost, I scrutinize the mechanism behind the VBC Volume-bias pattern in a simplified simulation model. This approach may neglect confounding factors present in empirical studies and how managerial action influences how resources are consumed over time (Banker & Byzalov, 2014). Hence, it is essential to consider the impact of managerial action and the resulting timely perspective on cost hierarchies, as other theories on cost behavior suggest (Banker et al., 2018). Future research is encouraged to investigate the effect of these characteristics on the emergence of the investigated pattern. Moreover, because empirical proof of the existence of a cost hierarchy is limited (Banker et al., 2021b), contemporary cost accounting argues that the traditional fixed and variable cost structure may be more accurately reflecting typical resource consumption (Anderson & Sedatole, 2013). Since I did not incorporate this in the investigation, further research is needed to better understand the relationship between activities and overhead costs. Nevertheless, the findings will provide a solid stepping-stone for these considerations and guide future empirical and simulation-based research on this topic.

6 PRODUCT-LEVEL ERRORS: UNDERSTANDING OF OVER- AND UNDERCOSTING[52]

6.1 INTRODUCTION

Prior cost accounting studies focused on providing relevant insights into how costing system design and resource consumption affect the system-level error of a costing system, which is the sum or average error in reported costs for all products in a given product portfolio (Labro, 2019) (see Figure 3). The system-level error is a good indicator of the overall efficacy of the design of a costing system, but it does not provide any information about the errors in costs of single products (i.e., the product-level error) (Labro & Vanhoucke, 2007). In contrast, for decisions made based on product costs (product-based planning), single product costs and therein, product-level errors appear as the more critical information than total costs or total errors of the portfolio (Gupta & King, 1997; Moriarity, 2005). Hence, the product-level error is likely a relevant aspect to improve decision-making. More precisely, understanding which products are overcosted or undercosted and by which magnitude can aid in detecting unprofitable products or set prices (Anand et al., 2017).

This chapter's objective is to provide an understanding of the error in single-product costs caused by limited information cost allocation. Hence, this chapter primarily aims to investigate the patterns of product cost cross-subsidization (CSB1, CSB2, CSB3) from Table 4.

I conduct numerical experiments based on the simulation model in Schmidt et al. (2023) (i.e., the model in Chapter 5) to investigate the cost allocation error for each product. Using this experimental design, I follow different steps to achieve the chapter’s overall goal of providing a better understanding of errors in single products’ costs. First, I investigate whether the system-level error distributes unevenly across the single products in the portfolio, with different products carrying different errors in their costs. This would emphasize the importance of product-level errors instead of system-level errors in product-based planning. Second, I aim to scrutinize the mechanism behind product-level errors and over- and undercosting. I disentangle the different error types (i.e., aggregation and specification error; see Figure 3) and measure which error type contributes to the error in the final product costs. Third, based on the identified mechanism, I aim to provide practical guidance to identify and reduce product cost errors. I

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[52] This chapter is based on the unpublished working paper “Product-specific costing errors: Unpacking the mechanism of over- and undercosting” (working title) by Lasse Kehrhahn, Matthias Meyer, and Mark Schmidt.

relate observable product characteristics to the unobservable error to determine which characteristics signal a product's higher probability of being under- or overcosted. I identify these product characteristics from priorly identified patterns (e.g., CSB1 and CSB2 from Table 4) and the specified mechanism. More precisely, I suspect that a product's *production volume, number of resources consumed, sum of allocated costs, the usage of cost-wise large cost drivers*, and *fraction of available cost drivers* are observable characteristics that potentially indicate large product-level errors.

The results highlight that, indeed, the system-level error disproportionally concentrates on a few highly inaccurately costed products. More specifically, the 10% most inaccurately costed products in a product portfolio account for roughly one-third of the system-level error. Interestingly, this proportion remains equal or even increases with more refined costing systems. Consequently, planning based on reported costs is particularly detrimental for the affected products, which cannot directly be resolved by refining the costing system. This illustrates the importance of the product-level error instead of the system-level error for cost-based decision-making.

By specifying the mechanism behind product-level errors, I find that the aggregation error does not directly increase the final error but mainly the specification error, which then manifests the final product-level error. This extends the prior understanding of interactions between errors in cost allocation (Labrou & Vanhoucke, 2007) (Figure 3) and shows how the specification error is the main driver behind product-level errors but also requires the aggregation error to occur.

Concerning the observable product characteristics, I find that *production volume*, the *sum of allocated costs*, and *the usage of cost-wise large cost drivers* positively relate to the product-level error. Consequently, products with high (low) specifications in these characteristics have a higher probability of being overcosted (undercosted). The *number of resources consumed*, and *the fraction of available cost drivers used* exert no strong relation to the product-level error. These results partially remedy the challenge of product-level errors by identifying product characteristics that can indicate when a product is likely over- or undercosted. Thus, practice is guided to be cautious when making decisions based on these product's costs. In that regard, the results also illustrate that information about cost driver usage (e.g., the usage of cost-wise large cost drivers) taken from the costing system can be helpful for decision-makers to improve their understanding of allocated costs (Mastilak, 2011). Additionally, these results show that the VBC individuality-bias (CSB2) is likely only driven by the VBC volume-bias (CSB1), as the individuality of a product does not relate to its over-or undercosting. Moreover, this chapter develops two new cost-driver selection heuristics that outperform the commonly used

BIGPOOL heuristic and are relevant for practice.[53] Lastly, I apply the approach to a case study of a German valve manufacturer and show how empirical data can be used to investigate empirically unobservable cost allocation errors by combining them with numerical experiments. In summary, the innovation of this chapter is to examine the error in the reported costs for single products rather than for an entire portfolio and to link these to observable determinants to support product-based planning.

6.2 PRIOR CONSIDERATIONS

The focus in this chapter is on errors in a single product's costs that result from the usage of limited information costing systems and affect cost-based decision-making (see Figure 3). It is, therefore, essential to understand how firms employ product costs as condensed economic information for product-based planning decisions (Krishnan, 2015) to identify conditions where errors affect such decisions and where not. In that regard, and opposed to prior studies (Balakrishnan et al., 2011) and Chapters 4 and 5, this chapter aims to shift the argumentation from the system-level error to the product-level error. Understanding the overall system-level error helps evaluate the efficacy of a costing system design (Labro, 2019) but only provides limited insights into where costing errors caused by the costing system are detrimental to product-based planning. Interestingly, most studies and identified patterns in errors in product cost information focus on the system-level error instead of the product-level error[54], despite its importance for product-based planning. In the following, I elaborate on product-based planning and instances of detrimental product-level errors.

6.2.1 PRODUCT-BASED PLANNING

Product-based planning involves setting prices and capacities to maximize profits (Balakrishnan et al., 2012a; Demski, 2008). For this, firms are required to assess the consumption of different resources by different products in the portfolio to build capacities by estimating demand given required prices that cover costs and maximize profits (Balakrishnan & Sivaramakrishnan, 2002; Banker & Hughes, 1994). Product costs carry aggregated and easily shareable information about products' overall resource consumption (Mertens, 2020) and are thus highly relevant for product-based planning. More specifically, product costs are used to determine prices that provide sufficient contribution margins (Homburg et al., 2018). Having identified desirable prices, a firm can estimate the required capacities to produce products in

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[53] See Chapter 4 for a detailed investigation of different design heuristics.

[54] For instance, Table 4 lists nine patterns regarding the system-level error, compared to three patterns regarding the product-level error. Additionally, numerical and empirical observations appear scarcer for these patterns.

the corresponding quantities (Banker & Hughes, 1994). This process involves many uncertainties that have been subject to operations research (Dierynck & Labro, 2018b), which usually assumes that product costs are known to a firm. Instead, I follow Balakrishnan et al. (2011) and argue that obtaining product costs is an informationally demanding process and usually results in erroneous product costs (Datar & Gupta, 1994) because product costs result from a limited information costing system that can only approximate true resource consumption (Labro, 2006a). As a consequence, product-based planning is corrupted due to inaccurate product costs.

6.2.2 CONDITIONS OF DETRIMENTAL PRODUCT-LEVEL ERRORS

In a multi-product firm, the error in reported costs arises as some products are accounted for the costs of other products because the costing system wrongly determines the consumption of costly resources (Horngren et al., 2015). Hence, some products in the portfolio erroneously carry the costs of other products. This is known as product cost cross-subsidization (Schmidt et al., 2023). More formally, the reported costs of a product differ from the true costs of a product with $PC_{reported} = PC_{true} + \varepsilon$, where ε is an error that is greater or smaller than zero (also see Chapter 2.2.2). To evaluate the efficacy of a costing system design in terms of the achieved system-level error, prior research summed or averaged ε over all products in a firm's portfolio (Labro & Vanhoucke, 2007). This introduces shortcomings for the consideration of ε in a single product. First, the aggregated measures usually do not differ between the sign of ε, or in other words, whether the product is over- or undercosted. Second, the aggregation weighs different magnitudes for a single ε equally. That is, smaller values for ε equally contribute to the system-level error as larger values for ε although larger values may be over-proportionally detrimental to product-based planning. For instance, Kaplan and Atkinson (1998) propose the materiality threshold in product cost errors at a 5% deviation from true product costs. Following this reasoning, a below 5% error ε in all products of a portfolio would be negligible for any product-based planning decisions. Instead, a 10% error ε in only a subset of products in the portfolio may result in a lower average of all errors ε (i.e., lower system-level error), but may be significantly detrimental to product-based planning.

Concerning the two major tasks of product-based planning – setting prices and determining resource quantities – instances with detrimental product-level errors arise in the following exemplary settings. Suboptimal prices are set if the product is undercosted so that the desired prices are below the true costs of a product: $PC_{true} > Price > PC_{reported}\, with\, \varepsilon < 0$. Regarding overcosting, resource quantities and corresponding capacities are under-acquired if reported product costs exceed true product costs because estimated demand is underestimated for the too high prices: $Price > PC_{reported} > PC_{true}\ with\ \varepsilon > 0$. Collectively, the magnitude and direction of the error ε for single products play pivotal role for product-based planning. Given the efforts required to update and design more information-demanding costing systems, (Anand et al., 2014) reducing the system-level error to decrease all product-level errors ε, to be non-materialistic is likely uneconomically (Balakrishnan et al., 2011). This is further hampered by the error being empirically unobservable (Labro, 2006a). Thus, a firm is usually unaware of which products are substantially under-or overcosted (Cooper & Kaplan, 1999) and cannot evaluate their costing system refinement based on that.

6.2.3 CAUSE OF PRODUCT-LEVEL ERRORS

Referring to Chapter 2.2.2 errors in product costs both at the system-level and product-level stem from the three error types – aggregation error (AE), specification error (SE), and measurement error (ME). These error types arise because a costing system aggregates information about true resource consumption by employing a cost driver which's consumption pattern ought to accurately reflect the consumption of multiple resources (i.e., cost driver usage) (Datar & Gupta, 1994).[55] Due to this averaging effect, the cost driver usage underemphasizes true resource consumption for some products and overemphasizes it for others, resulting in under- and overcosting.[56] In other words, products that deviate profoundly from the average consumption that the cost driver displays have a higher probability of deviating from their true costs compared to products that have an average consumption in general and in the cost driver as well. Certain product characteristics specify and influence the underlying resource consumption, indicating whether a product consumes below or above average of specific resources and costs. Consequently, products that deviate from the average specification of a product characteristic that influences resource consumption also have a higher probability to deviate from their true costs. For instance, Chapter 5 shows that in volume-based costing systems, high-volume products are overcosted, and low-volume products are undercosted. This is because the volume-based cost driver (e.g., production volumes) overemphasizes resource consumption for high-volume products compared to low-volume products. In settings where true resource consumption follows this pattern (e.g., where all costs vary proportionally with production quantities), this cost driver computes accurate product costs. However, in settings

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[55] Chapter 2.1 elaborates in more detail about the structure and functionality of a costing system.

[56] Additionally, the measurement error contributes to the deviation of the resource consumption displayed in the cost driver from the true resource consumption (Cardinaels & Labro, 2008). As in Balakrishnan et al. (2011) I do not focus on the measurement error as I found its effects intuitive.

where resource consumptions do not increase with higher production volumes (e.g., where a large fraction of costs are decoupled from production quantities), this approach results in cross-subsidization and larger product-level errors ε. Thus, due to the combination of a volume-based cost driver and volume-independent resource consumption, products with the characteristic high (low) volume contain a large overcosting (undercosting) error.

This under- or overemphasizing of the resource consumption of a single product by the costing system is reflected in a positive or negative specification error *SE* in the cost driver. The specification error *SE* occurs when a wrong percentage of a resource cost is allocated to a product (Labro & Vanhoucke, 2007). In other words, the selected cost driver is not optimal in representing the underlying resource consumption (Datar & Gupta, 1994). A product's theoretically optimal cost driver rate is the average percentage rate of all resources consumed within a cost pool.[57] If that is given, there is no systematic over- or underemphasizing bias of the cost driver for the resource consumption within a cost pool for a particular product. Consequently, firms aim to identify cost drivers that represent resource consumption most accurately to reduce *SE* (Homburg, 2001). In that context, the probability of selecting a more fitting cost driver increases if the cost pool’s resource consumption is homogeneous (Gupta, 1993). This homogeneity can be described by the aggregation error *AE*, which specifies whether, within the cost pool, resource consumption follows different patterns (Datar & Gupta, 1994) (also see Chapter 2.2.2). This can result in variations in the relative consumption of different resources for a single product, impeding the selection of a representative cost driver. Consequently, *AE* increases the potential for high *SE*, while *SE* manifests the product-level error. Figure 27 shows a conceptual example that illustrates the two concepts of *AE* and *SE* and how they result in under- or overcosting for different products.

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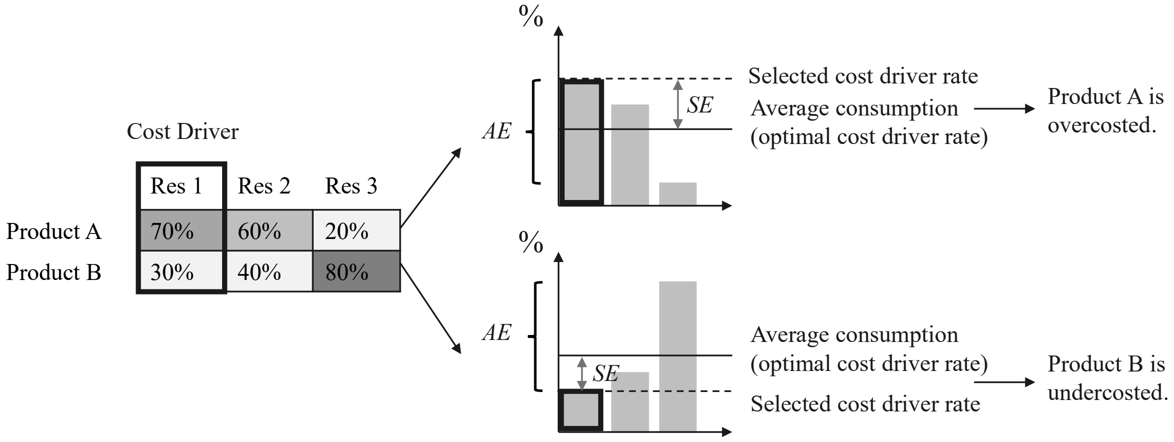
[57] Note that the respective costs of a resource interact with this. That is, a deviation between the percentage cost driver rate and the average percentage consumption can be outweighed if there are costly resources from which the product consumes percentages that also deviate significantly from the average. In these cases, not the average, but a percentage closer to the value of that resource(s) is optimal. For several reasons, I continue with the perspective on percentage consumption instead of factoring in the resource costs. First, cost driver rates in empirical costing systems are often percentage values (Cardinaels & Labro, 2008). Second, factoring in resource costs into the calculation of *SE* would result in a large overlap between the percentage error *PE* and specification error *SE*. Corresponding results between *SE* and *PE* would be tautological (Balakrishnan & Penno, 2014). Lastly, an outweigh of *SE* based on percentage consumption by resource costs would only arise in settings with high disparity in resource costs and, therefore, likely only in less common scenarios (Balakrishnan et al., 2011).

Figure 27. Conceptual example of the over-and undercosting mechanism in product-level errors



Note. *AE* = Aggregation error; *SE* = Specification error; *Res* = Costs of a specific resource.

In summary, awareness for systematic distortions (i.e., whether a product is under-or overcosted) potentially allows for counter-steering in product-based planning. In other words, identifying combinations of costing system designs, resource consumption patterns, and observable product characteristics that result in profound upward or downward product-level errors, can aid in adjusting prices or setting capacities. Costing systems generally follow a similar averaging-characteristic, and patterns in indirect resource consumption have been theorized and investigated several times (Anand et al., 2019; Anderson & Sedatole, 2013), hence it can be argued that some product characteristics generally indicate profound product-level errors. One objective of this chapter is to test this expectation.

6.2.4 PRODUCT CHARACTERISTICS

Product characteristics refer to empirically observable determinants of an individual product that specify a product's position in a firm's product portfolio and provide descriptive information about relevant performance indicators, such as the production volume, indirect costs, and other quantifiable specifications (Balakrishnan, Pugely, & Shah, 2017). Only a few earlier studies provide the first indications of relevant product characteristics that interfere with costing system design towards an under- or overestimating of true resource consumption (Schmidt et al., 2023).

I employ the above-suspected mechanism from Figure 27 to determine characteristics that potentially indicate a large over- or undercosting of respective products. Additionally, I draw upon prior observations on misestimation of product costs and link these to typical specifications of product portfolios (e.g., cross-subsidization patterns from Table 4). Generally, I assume a multi-product firm produces various products with several characteristics to address different customer needs (Kekre & Srinivasan, 1990). Common customer needs are addressed by standard products and exotic customer needs by more individualized products (Lancaster, 1990). The degree of individualization or standardization determines different product characteristics that, in turn, result in different resource consumption patterns and a higher or lower probability for over- or undercosting by a given costing system. For instance, standard products are regarded as less resource-intensive (ElMaraghy et al., 2012) and easier to produce (Anderson, 1995; Fisher & Ittner, 1999), because they consume fewer resources in lower magnitudes (Cardinaels & Labro, 2008; Kaplan & Cooper, 1998b). Consuming more and different resources or activities, such as customer-service efforts, should impede accurate cost allocation for a single product, simply because greater measurement efforts are required (Cardinaels & Labro, 2008). This assumption is also displayed in the CSB2 pattern in Table 4, which reports the conceptual consideration of prior studies that the costs of individualized products are underestimated compared to standardized products (Schuh, Rudolf, & Vogels, 2014). Hence, I determine the *number of different resources consumed* as the degree of individualization to be a relevant product characteristic to identify products with large product-level errors and potential overcosting. Arguably, firms may not be aware of the precise number of consumed resources or activities of a single product but likely have a general idea of which products evoke additional efforts and which not (Balakrishnan et al., 2011).

Standard products often come with larger production quantities (Rezaie et al., 2008), which results in increased unit-level resource consumption (Anderson & Sedatole, 2013), which in turn, results in a higher relative consumption of such resources and positive specification errors, if total resource consumption does not correlate with production volumes (Schmidt et al., 2023). Thus, high production volumes would correlate positively with the probability of a product being overcosted. Hence, the *production volume* of a product appears as a relevant observable characteristic. This also allows to relate to prior discussions on cross-subsidization in volume-based costing systems, although the modeled costing system rather reflects an ABC system (Schmidt et al., 2023).

Prior studies posit that the structure of a costing system provides further valuable information beyond reported product costs (Booker et al., 2007; Joshi, Krishnan, & Lave, 2001; Mastilak, 2011). Hence, additional observable characteristics can be extracted from the costing system that potentially help determining over- and undercosted products. Based on the expected mechanism in Figure 27, positive specification errors (i.e., overcosting) occur if the relative cost driver rate exceeds the actual relative consumption of resource costs within a cost pool.

Consequently, I assume that products that receive relatively higher indirect costs by the costing system are more likely to be overcosted. Prior studies noted that more costly products tend to have large cost errors (Gupta, 1993). To simplify this characteristic, it can be worthwhile to focus only on cost-wise large cost pools and assess their relative consumption (i.e., cost driver rates). In sum, I expect products with relatively large (small) values for the *sum of allocated costs* and the *the usage of cost-wise large cost drivers* to be profoundly overcosted (undercosted). Additionally, I expect that products that use a larger *fraction of available cost drivers* have a smaller product-level error because the increased number of cost drivers reduces the degree of aggregation with which the costing system resembles the true resource consumption and, therefore, reduces the specification error *SE* of that product. In summary, this chapter determines the *production volumes, number of resources consumed, sum of allocated costs, usage of cost-wise large cost drivers,* and *fraction of available cost drivers* as observable characteristics of a product, potentially indicating large product-level errors.

6.3 MODEL AND SIMULATION PROTOCOL

To investigate product-level errors in cost allocation, I conduct numerical experiments based on the simulation model derived from Schmidt et al. (2023). More specifically, I employ the model from Chapter 5 with the simple cost hierarchy that distinguishes between unit-level and non-unit-level resources and costs. [58]

The model generates production environments for product portfolios with 50 products (*NUMB_PRO*), which differ in the consumption of 50 resources (*NUMB_RES*). Each product comes with a specific production volume (*ProductVol),* which is used to reflect heterogeneity within a product portfolio (Anderson, 1995; Schoute, 2011). The model draws the demand for each product *ProductVol* from a logarithmic normal distribution with the factor *Q_VAR* being the standard deviation on the log scale. This allows a Pareto-similar distribution of production quantities, with different degrees of disparity, to account for the differentiation of high-volume and low-volume products within the firm's portfolio.[59]

The resource cost vector *RCC* indicates the distribution of the total costs *TC = 1.000.000* to the individual resources. In line with prior studies, the model distinguishes between unit-level resources, such as production activities that apply to every single unit, and non-unit-level

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[58] See Chapter 5 for a more detailed model description and Chapter 9.6 in the appendix of this thesis for a numerical example that explains the modeling approach.

[59] A Pareto-similar distribution of production volumes is for instance reported in Rezaie et al. (2008).

resources, that are decoupled from unit production (Cooper & Kaplan, 1991). This creates different consumption patterns of different tiers in a simple cost hierarchy that significantly affects the accuracy of a costing system (Balakrishnan et al., 2011; Schmidt et al., 2023). I determine 25% -45% of the *NUMB_RES* resources to be unit-level resources that account for 45% to 65% of total costs *TC*. These fractions are based on the review of empirical studies in Chapter 2.3. For each subsection of vector *RCC*, the model draws random values from a logarithmic-normal distribution, with *RC_VAR* being the standard deviation on the log scale drawn randomly between 0.5 and 1.5. It then normalizes the subsections to account for their respective share of *TC*. Thus, the resource cost vector *RCC* can have different degrees of disparity while meeting the cost share requirements for unit- and non-unit-level costs. A high disparity may resemble a strong focus on a particular technology or core activity, such as a mass production facility (Anand et al., 2019; Kerremans et al., 1991). With low disparity, many resources are valued equally in monetary terms, which might apply to a firm that produces various products that consume different resources (Balakrishnan et al., 2011).

The variety of unique resource consumption patterns specified by the matrix *RES_CONS_PAT* is determined by its density *DENS* (share of zero entries of *RES_CONS_PAT*) and its similarity between consumption patterns of the individual resources (i.e., the columns of *RES_CONS_PAT*). As a final specification of *RES_CONS_PAT*, the model distinguishes between unit- and non-unit-level resource consumption pattern in alignment with the specified fractions in *RCC*. The unit-level (non-unit-level) resource consumption patterns are generated based on an input correlation of *COR1* (*COR2*). High values for *COR1* and *COR2* describe similar production processes with strongly correlated resource consumption, while resource consumption becomes increasingly dissimilar as the discrepancy between the two parameters increases. Additionally, unit-level resource consumptions (i.e., entries in *RES_CONS_PAT*) are multiplied by the corresponding production volumes to follow the proposition that single-unit production activities cause unit-level costs. The non-unit-level fraction in *RES_CONS_PAT* is therein not multiplied by the production volumes. This is also in line with the modeling in Chapter 5 and in Schmidt et al. (2023).

The costing system is designed as a two-stage allocation process through forming cost pools (*CP*) and selecting cost drivers (Labro & Vanhoucke, 2007). First, the model groups costs into cost pools by seeding the *CP* -1 cost-wise largest resources into a cost pool and allocating additional resources to the seeded resources based on the correlation of their resource consumption.[60] Next, for every *CP*, a cost driver is selected using the *BIGPOOL* method. The method identifies the largest cost-wise resource of each cost pool and determines its relative consumption to be the cost driver.

6.3.1 OPERATIONALIZATION OF PRODUCT CHARACTERISTICS

Production volumes, *number of resources consumed*, *sum of allocated costs*, *usage of cost-wise large cost drivers*, and *fraction of available cost drivers* are determined as observable characteristics of a product, that potentially help to identify products with large product-level errors. The *production volumes* of a product and the number of consumed resources may be available to the manager by the ERP system or bill of materials (Anand et al., 2023; Balakrishnan et al., 2011). This model directly models a product's production volumes by defining the variable *ProductVol*. For the *number of resources consumed*, I count the nonzero entries in *RES_CONS_PAT* for each product (row), resulting in the variable *NumbRes,* which reflects the breadth of resource consumption and degree of individualization.

Since the true resource consumption across all resources is unobservable for the firm (Dopuch, 1993), the focus is on information that can be taken from the costing system. First, the reported product costs *PCH* resemble the *sum of allocated costs*, as I assume that direct costs can be traced error-free to single products (Hwang et al., 1993). In the model, *PCH* is reported by the costing system. The *usage of cost-wise large major cost drivers* is obtained by calculating the average relative consumption of cost drivers that allocate more than 20% of *TC* (i.e., \$200,000)[61], resulting in the variable *consBigDriver*. Last, the model computes the fraction of available cost drivers similarly to *NumbRes* and counts the number of nonzero entries in the usage of all cost drivers for each product and divides this number by the available number of cost drivers (i.e., number of cost pools in the costing system). This provides the variable *NumbDriver*.

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[60] In the original model, Anand et al. (2019) implemented four different heuristics for assigning resource costs to cost pools: (1) Size-Miscellaneous (SM), (2) Size-Correlation-Miscellaneous (SCM), (3) Size-Random–Miscellaneous (SRM), and (4) Size-Correlation-Miscellaneous-CutOff (SCMC). From these heuristics, I employ (2) the Size-Correlation-Miscellaneous heuristic, because grouping costs based on size and similarity appears as an intuitive approach that likely follows practice. Apart from that, I conducted robustness analyses with other heuristics and found the results to remain qualitatively equal.

[61] I selected 20% of total costs because surveys show that many firms employ five or fewer cost drivers to allocate indirect costs (Al-Omiri & Drury, 2007; Drury & Tayles, 2005). Thus, cost drivers that allocate this fraction appear likely to occur in practice. Additionally, I tested for robustness with other values for this setting (i.e., 10% and 30% of *TC*) and found our results to be qualitatively robust.

6.3.2 DESIGN OF EXPERIMENTS

I employ the described model with the above input, control, and output variables. Table 20 overviews the settings following the design of experiments approach described by Lorscheid et al. (2012). The main input variables are the degree of resource sharing *DENS* and the number of cost pools *CP*. Hence, I aim to model different production environments with different degrees of costing system refinement. For every unique combination of the input variables of the production environment, the model generates 200 randomly generated firms. To each of the resulting 600 randomly generated firms, the model applies every costing system design (i.e., number of cost pools) and obtains 3,600 firm-level observations and 180,000 product-level observations in total.

Table 20. Design of experiments

Input variables		**Control variables**		**Output variables**
Production Environment				
DENS Density of RES_CONS_PAT	0.25; 0.5; 0.75	*Q_VAR* Disparity in production quantities	U[0.5;1.5]	*PCB* Benchmark costs of a cost object
Costing System		*RC_VAR* Share of costs that are assigned to the “big” resources	U[0.5;1.5]	*PCH* Reported costs of a cost object
CP Number of Cost Pools	*1,3,6,10,15,20*	*COR1* Correlation between volume resources	U[-0.2,0.8]	*Percentage Error (pe)* *PE* = (PCH – PCB)/PCB
		COR2 Correlation between batch resources	U[-0.8,0.2]	*Absolute percentage Error (ape)* *APE* = abs(PCH – PCB)/PCB
		Costing System		*EUCD* Euclidean Distance as the overall error of the costing system (Balakrishnan et al., 2011)
		CP-Heuristic Heuristic to allocate resources into cost pools	*SCM*	*%ACC* Share of accurately costed products, where reported product costs are ± 5% different from true product costs (Kaplan & Atkinson, 1998).

Table 20 (continued).

	CD-Heuristic Heuristic for cost-driver selection	*BIGPOOL*	*ErrorDisp* Share of EUCD caused by the 10% most inaccurate products
			AE Aggregation Error per product
			SE Specification Error per product
			UC_share Share of materially undercosted products from 1-*%ACC*.
			ProductVol Production quantities per product
			NumbRes Number of resources consumed
			consBigDriver Relative consumption of cost pools that aggregate at least 20% of total costs
			NumbDriver Fraction of available cost drivers used

Note. Unique production environments: 3*200 = 600; Unique costing system designs = 6; Number of firm-level observations = 600*6 = 3,600; Number of product-level observations = 3,600 * 50 = 180,000

Table 20 also lists the employed output variables. The main variables to measure the product-level error is the percentage error *PE* between true product costs *PCB* and reported product costs *PCH*, describing the size and direction of the error (i.e., overcosting or undercosting) (Christensen & Demski, 1997). *APE* reports the absolute percentage error, neglecting its direction. Additionally, I aim to scrutinize how the system-level error distributes along single products into product-level errors. Thus, I compute *EUCD* as the system-level error (i.e., the sum of misallocated costs) and *%ACC* as the share of accurately costed products (i.e., *PE* is within ± 5%), following Balakrishnan et al. (2011). As described above, products with profound product-level errors are most detrimental to product-based planning. I therefore compute the share of EUCD that is contributed by the 10% most inaccurately costed products (*ErrorDisp*).[62] Lastly, undercosting and overcosting may have different determinants and effects on product-based planning. Thus, I calculate the share of materially undercosted products from all

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[62] Since, the modeled production environment always consists of 50 products, 10% are five products.

materially falsely costed products (*UCShare*) and the mean absolute percentage error (*MAPE*) for overcosted and undercosted products, respectively.

To operationalize the mechanism behind over- and undercosting I measure the aggregation error *AE* of every single product as the standard deviation within its relative resource consumption across all resources within a cost pool. I weigh this standard deviation with the cost size of the cost pool and average it to obtain one value for each product. The specification error *SE* for a product is operationalized as the difference between the selected cost driver percentage from the theoretical optimal percentage (i.e., the average). This is calculated for every cost pool and, similar to *AE*, weighed with the cost size of the cost pool and averaged over all cost pools. Therefore, both *AE* and *SE* are at the product level and differ from the measures applied by Labro and Vanhoucke (2007).[63] Finally, I observe the operationalized product characteristics *PCH, ProductVol, NumbRes, consBigDriver, NumbDriver*, as described in Chapter 6.3.1.

6.4 RESULTS

6.4.1 DISTRIBUTION OF PRODUCT-LEVEL ERRORS IN THE PRODUCT PORTFOLIO

In the first analysis of the numerical experiment, I investigate the distribution of the system-level error across the whole portfolio to connect these findings to the prior studies. Table 21 shows that, in line with previous studies (see references of patterns CSD1 and RC4 in Table 4), a greater degree of resource sharing and a more refined costing system with more cost pools generally decreases the system level error, as measured by *EUCD* and *%ACC* (Balakrishnan et al., 2011). Figure 28 Panel A and Panel B illustrate the concave progression of the system-level error, as observed priorly (Anand et al., 2019). The similar behavior of this model compared to prior models illustrates a comparable base that allows to connect the results to prior studies (Thiele & Grimm, 2015).

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[63] Labro and Vanhoucke (2007) employ the number of cost pools to measure the aggregation error and an artificially introduced measurement error on the cost driver to induce the specification error. Compared to these measures, the measures applied here are not exogenously determined by the modeler but arise endogenously (Anand et al., 2019).

Table 21. Descriptive statistics of system-level error measures

Panel A: Degree of Resource Sharing

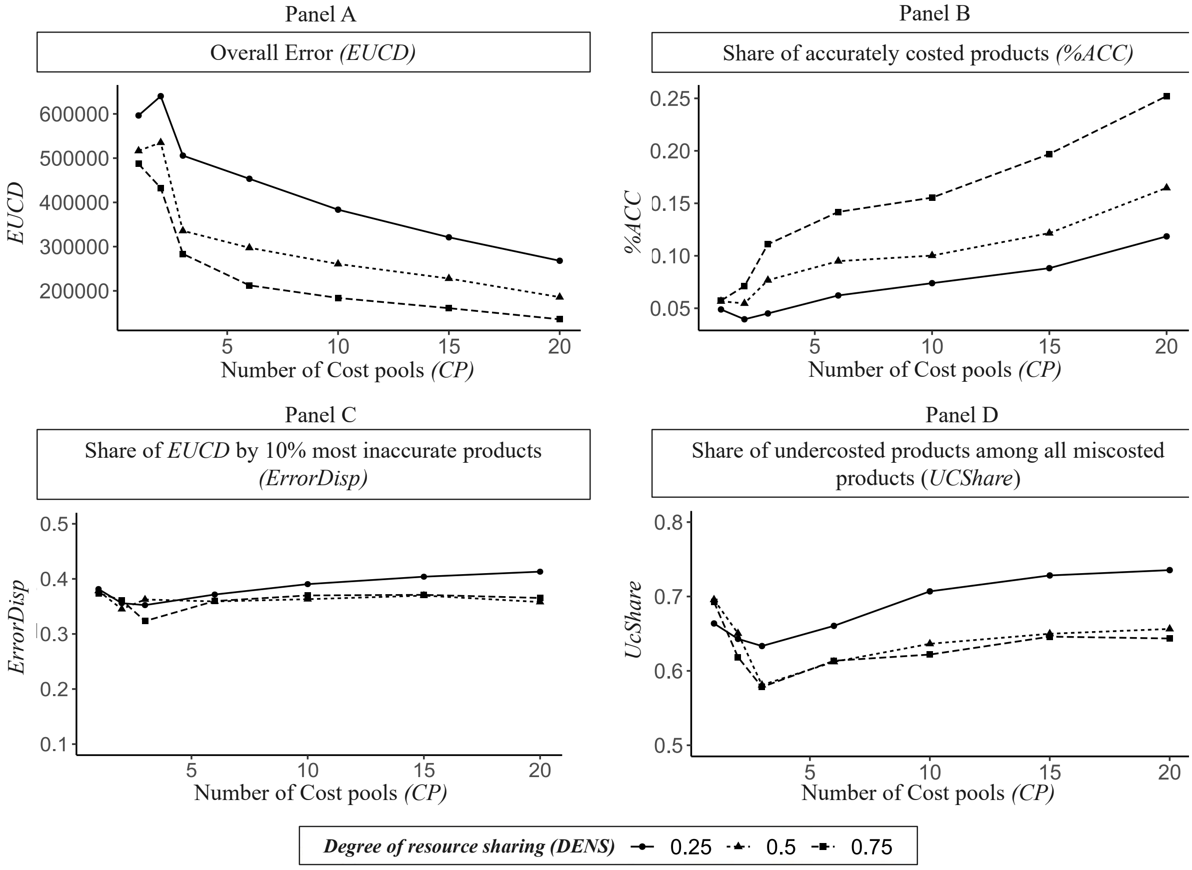
		Average Values			
Density of resource consumption matrix (*DENS*)	Units	Global Average	Little sharing of resources (*DENS* = 0.25)	Medium sharing of resources (*DENS* = 0.5)	High Sharing of resources (*DENS* = 0.75)
System-level Error (*EUCD*)	€	396390	510320	379061	299787
Share of accurately costed products (*%ACC*)	Percent	0.08	0.07	0.08	0.11
MAPE of overcosted products	Percent	0.54	0.81	0.48	0.34
MAPE of undercosted products	Percent	0.36	0.43	0.35	0.29
Percentage of *EUCD* caused by top 10% products (*ErrorDisp*)	Percent	0.34	0.36	0.33	0.32
Share of undercosted products (*UCShare*)	Percent	0.65	0.68	0.65	0.63

Panel B: Number of Cost Pools

Refinement of Costing System (Number of Cost Pools, *CP*)	Units	Global Average	Single-Cost Pool (*CP* = 1)	Medium number of Cost Pools (*CP* = 10)	High number of Cost Pools (*CP* = 20)
System-level Error (*EUCD*)	€	396390	593178	333239	260063
Share of accurately costed products (*%ACC*)	Percent	0.08	0.05	0.09	0.12
Mape of overcosted products	Percent	0.54	0.75	0.48	0.44
Mape of undercosted products	Percent	0.36	0.50	0.32	0.22
Percentage of *EUCD* caused by top 10% products (*ErrorDisp*)	Percent	0.34	0.36	0.32	0.38
Share of undercosted products (*UCShare*)	Percent	0.65	0.67	0.64	0.71

Note. *CP* = Number of cost pools; *DENS* = Degree of resource sharing.

Figure 28. Distribution of the system-level error



Note. *EUCD* = Euclidean distance between all benchmark and reported product costs and measure for the overall (system-level) error.

Table 21 reveals a heterogeneity in error distribution across different products. The mean absolute percentage error (*MAPE*) is significantly higher for overcosted products than undercosted ones. Hence, overcosting appears more prevalent for being detrimental to product-based planning decisions. This disparity decreases with a greater degree of resource sharing. However, more cost pools generally result in lower average errors but not in a more even distribution for overcosted and undercosted products. This is further shown by the share of undercosted products from all materially falsely costed products (*UCShare*), which averages at around 65% and increases with more than three cost pools (see Figure 28 Panel D). Thus, refining a costing system appears to reduce overcosting errors more dominantly than undercosting errors.

Finally, Table 21 and Panel C of Figure 28 show that the top 10% of the most erroneous products are responsible for more than 30% of the total errors observed in the costing system

(*ErrorDisp*)[64]. This disproportion indicates a significant concentration of inaccuracies within a small fraction of products, suggesting that errors are not uniformly spread out but are instead skewed towards certain products. Additionally, Panel C illustrates that this proportion further increases with more than three cost pools. Thus, from a product-based planning perspective, refining the costing system does not directly reduce the risk of detrimental product-level errors in certain products. This highlights the need to understand the mechanism behind over- and undercosting to identify highly erroneous products based on associated product characteristics.

6.4.2 THE MECHANISM BEHIND OVER- AND UNDERCOSTING

To better understand the mechanism behind over- and undercosting, I measure the influence of specification error SE and aggregation error AE on product-level errors, as measured by *PE* and *APE*. First, on the system-level error, I observe how *AE* and *SE* behave when the costing system gets refined (i.e., more cost pools are added). Figure 29 shows the standardized values for the three measures along an increasing number of cost pools.[65] It can be seen that although all three measures decrease with more cost pools, they are not linearly related. That is, *APE* can decrease slower or faster than *AE* and *SE*. This can be related to the interaction of the two error types (Labro & Vanhoucke, 2007), in which they could also offset each other, resulting in a lower overall error (*APE*). Additionally, Figure 29 illustrates that the aggregation error is not linearly connected to the number of cost pools (as assumed in Labro and Vanhoucke (2007)). Instead, it stresses the concave pay-off from adding more cost pools (also see Chapter 4.6.3). Lastly, Figure 29 highlights the high correlation between *AE* and *SE* as described in the assumed mechanism.

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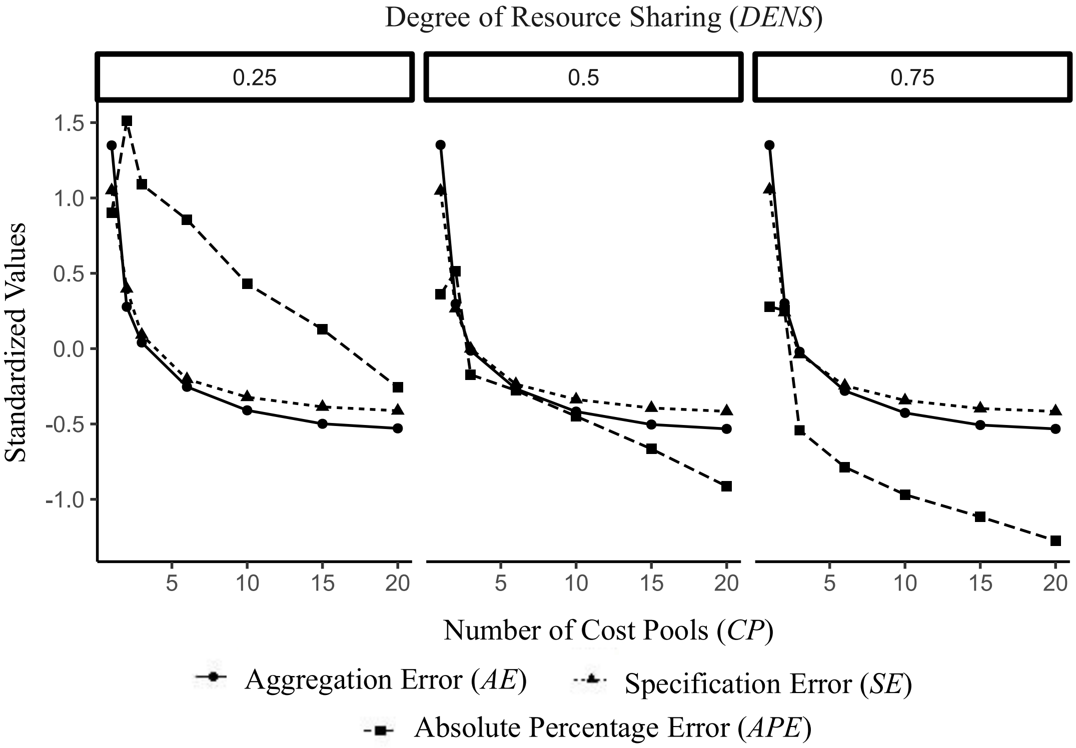
[64] For the top 20% of the most erroneous products this value increases to roughly 55%.

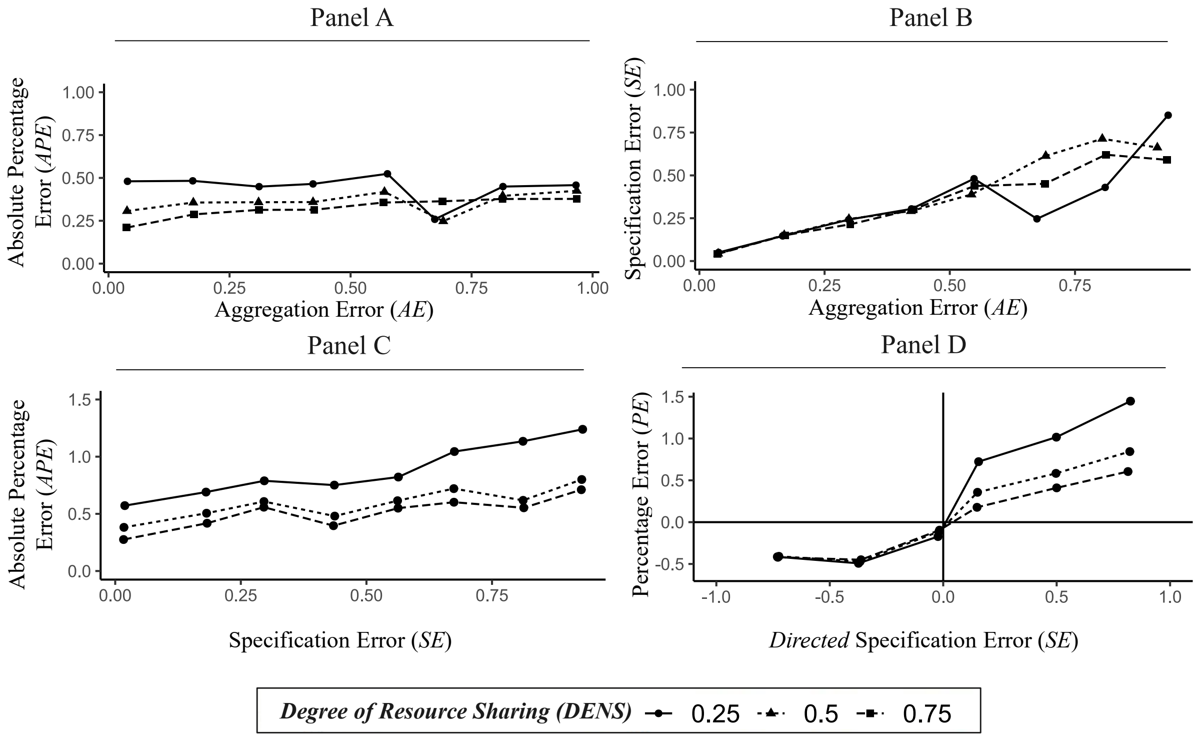
[65] I standardize the three measures to allow for an easier comparison in one scale.

Figure 29. Effect of the number of cost pools on different error types



Looking more closely into the interactions between aggregation error *AE*, specification error *SE,* and the product-level error (either *PE* or *APE*), Figure 30 Panel A shows that the aggregation error itself does not increase the *APE*. In other words, the aggregation error does not drive the product-level error, but it drives the specification error (Panel B of Figure 30). The specification error then drives the product-level error (Panel C of Figure 30; note the different y-axis), with high specification errors in products also having high absolute percentage errors. Moreover, when looking at the directed specification error (Panel D of Figure 30), which distinguishes between an upward or downward deviation from the optimal cost driver percentage, it becomes evident that the specification error determines a product's over- or undercosting (i.e., positive or negative percentage error). Consequently, products with positive specification errors are overcosted, and products with negative specification errors are undercosted.

Figure 30. Interaction between aggregation error, specification error, and product-level error



In summary, the results substantiate the expected mechanism, which describes that the few cost pools and inaccurate cost pooling result in an aggregation error of each product, which in turn increases the specification error. The specification error then determines which product's resource consumption is over- or underemphasized by the selected cost driver and therein over- or undercosted. Contrarily, prior studies have measured the aggregation error and specification error differently and observed a direct effect of the aggregation error on the product-level error. This is interesting because many findings proclaim the benefits of adding more cost pools as it reduces the aggregation error (see Table 4, CSD1 for references). Instead, these findings show that the aggregation error alone is not directly responsible for high errors in product costs, but the specification error.[66] Accordingly, the mechanism can be described as a mediation of the specification error on the relation between aggregation and overall product-level error. Using a causal mediation analysis, I examine this effect more closely. Figure 31 shows that the aggregation error significantly increases the specification error, which in turn increases the

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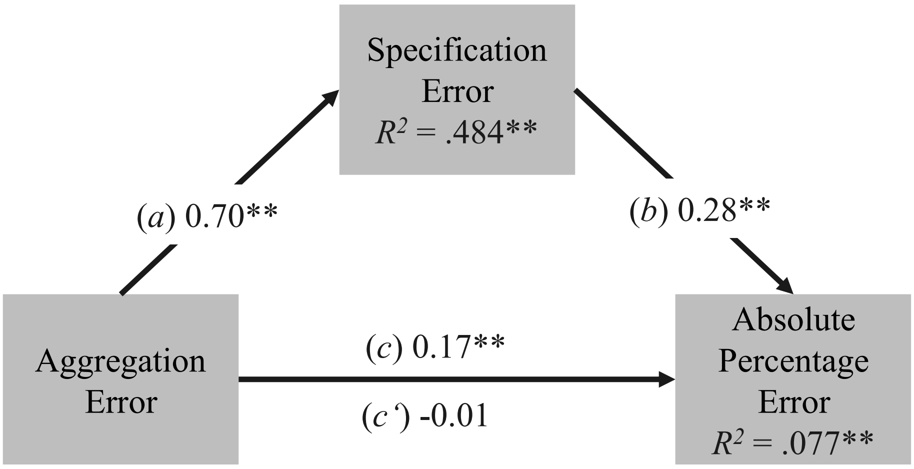
[66] To complete this discussion, I argue that the measurement error *ME* has a direct effect on the specification error as it simply further contributes to a deviation in cost driver percentages (Balakrishnan et al., 2011). Untabulated results show, that increasing or decreasing the measurement error has exerts trivial effects on the results and does not change these qualitatively. This is also in line with the observations in chapter 4.

absolute percentage error. In contrast, the direct effect of the aggregation error on the absolute percentage error is not significant (path *c'*). This, again, substantiates that the aggregation error only determines the potential for a specification error which then manifests into a product-level error.

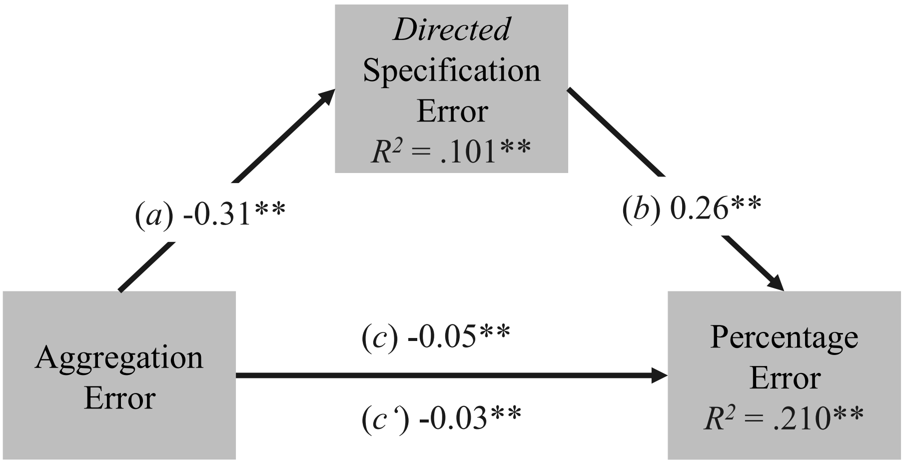
Figure 31. The mechanism behind product-level errors



Note. Path *c* describes the total effect of the aggregation error *AE* on the absolute percentage error *APE*. Path *c'* describes the direct effect of the aggregation error *AE* on the absolute percentage error *APE*.

I reconduct this mediation analysis with the directed specification error and the percentage error, which determines under-and overcosting of a product (Figure 32). Here I find that the total and direct effect of the aggregation error on the percentage error are significant but small. Instead, the aggregation error results in a negative directed specification error (path *a*), meaning dominant undercosting exists in highly aggregated costing systems. This is also in line with observations from Labro and Vanhoucke (2007) and pattern CSB3 from Table 4. The directed specification error significantly increases a product's percentage error. In other words, similar to panel D of Figure 30, products that are overemphasized by the cost driver (i.e., high positive directed specification error) are overcosted and vice versa.

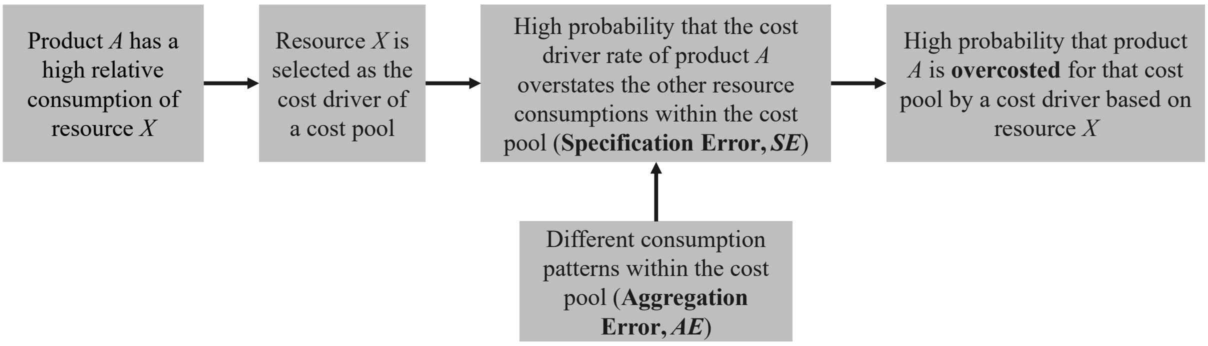
Figure 32. The mechanism behind over- and undercosting



Note. Path *c* describes the total effect of the aggregation error *AE* on the absolute percentage error *PE*. Path *c'* describes the direct effect of the aggregation error *AE* on the percentage error *PE*.

Overall, this determines the expected mechanism behind over- and undercosting and product-level errors and highlights the relation between the error types and the error in product costs. To summarize. Figure 33, summarizes the total process behind a particular product being overcosted.[67]

Figure 33. Process of overcosting



Starting with a high relative consumption of a resource that is then selected as the cost driver of a cost pool, the respective product receives an overstated fraction of the cost pool's costs because the cost driver overemphasizes the product's resource consumption. The aggregation error strongly drives this, resulting in an upward deviating specification error and the product's overcosting.

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[67] For simplification reasons, Figure 33 only describes a product's overcosting. The process can, however, easily be transferred to a product's undercosting.

6.4.3 CHARACTERISTICS OF OVER- AND UNDERCOSTED PRODUCTS

Based on the mechanism, I aim to identify connections between observable product characteristics and product-level errors to provide determinants that may signal a high probability for a product to be under-or overcosted. Table 22 overviews descriptive statistics for the modeled products and their characteristics. Panel A shows that there is a distinct variation between products due to their different characteristics. For instance, on average, a product is produced with a quantity of 20 units, which can increase to 647 or decrease to one unit (*ProductVol*). On average a product consumes 2% of a large cost driver's cost (*consBigDriver*), which can range up to 79%. Lastly, the average reported product costs (*PCH*) are slightly lower than the benchmark product costs (*PCB*), indicating the dominant undercosting in the costing system (see also Figure 28 and pattern CSB3 from Table 4) (Labro & Vanhoucke, 2007).

Table 22. Overview of characteristics of under- and overcosted products

Panel A: Single product characteristics

	Units	Min	Quartile 1	Median	Mean	Quartile 3	Max
ProductVol	Number	1	7	13	20.49	24	647
NumbRes	Number	3	15	25	25.53	36	48
PCB	€	74	800	1262	2322	2344	57674
PCH	€	23	646	1016	1981	1830	134991
NumbDriver	Number	0.05	0.40	0.66	0.64	0.9	1.00
consBigDriver	Percent	0.00	0.00	0.01	0.02	0.03	0.79

Panel B: Characteristics of under- and overcosted products (average values)

	Units	Global Average	Highly Undercosted (*PE* < -20%)	Undercosted (*PE* < -5%)	No Error	Overcosted (*PE* > 5%)	Highly Overcosted (*PE* > 20%)
ProductVol	Number	20	14	16	25	28	28
NumbRes	Number	26	25	25	27	25	25
PCB	€	2322	2650	2551	2184	1921	1902
PCH	€	1981	1190	1410	2180	3015	3327
NumbDriver	Percent	0.64	0.59	0.61	0.66	0.71	0.71
consBigDriver	Percent	0.02	0.01	0.01	0.02	0.04	0.05

Table 22 (continued).

Panel C: Pearson-Correlation of product characteristics and product-level error[1]

	ProductVol	*NumbRes*	*PCH*	*NumbDriver*	*consBigDriver*	*AE*	*SE*	*PE*
ProductVol	1	0.01	-0.18	0.01	0.52	0.00	0.38	0.11
NumbRes		1	0.01	0.54	0.02	-0.01	0.01	-0.05
PCH			1	0.09	0.13	-0.03	0.11	0.50
NumbDriver				1	0.12	0.32	0.09	0.14
consBigDriver					1	0.01	0.48	0.44
AE						1	-0.04	0.00
SE							1	0.37
PE								1

Note. *ProductVol* = Production volume of a product; *NumbRes* = Number of consumed resources; *PCB* = Benchmark product costs; *PCH* = Reported product costs; *NumbDriver*; Fraction of available cost drivers; *consBigDriver* = Usage of cost-wise large cost drivers. *AE* = Aggregation error; *SE* = *Directed* specification error; *PE* = Percentage error. [1] All correlations are significant p<0.05.

Panel B of Table 22 shows that (highly) undercosted and (highly) overcosted products profoundly differ in their product characteristics. Panel C of Table 22 illustrates how these different characteristics correlate with aggregation, specification, and percentage errors. In line with prior studies (Hwang et al., 1993; Schmidt et al., 2023), the production volumes of a product (*ProductVol*) are already a robust indicator of overcosting and undercosting. More specifically, (highly) overcosted products are produced in larger quantities than (highly) undercosted products. I understand that the high relative consumption of unit-level resources results in an overstate of high-volume products' resource consumption and, therefore, in overcosting. The presence of non-unit-level costs contributes to this result, as shown in Schmidt et al. (2023), by causing an aggregation error *AE*. Hence, this experiment also reproduces pattern CSB1 from Table 4. In contrast, a product's individuality displayed by the number of consumed resources (*NumbRes*) does not vary for under- or overcosted products. Engineering-oriented literature often describes that more individualized products tend to be undercosted while more standard products are overcosted (Elmaraghy et al., 2013). The number of parts or resources consumed is often employed as an approximation to measure the degree of individualization within a product (Fixson, 2005, 2006) because more specific customer needs can be addressed (Lancaster, 1990). The results of this experiment do not corroborate the conceptual considerations of prior literature that individualization itself relates to specific product-level errors (pattern CSB2). Instead, I argue that the driving force behind the undercosting of such products is caused by corresponding production volumes (*ProductVol*) that directly affect resource consumption.

Additionally, the results indicate an inverse behavior of benchmark product costs (*PCB*) and reported product costs (*PCH*). Panel B of Table 22 illustrates that the reported product costs increase with the percentage error *PE*, resulting in high-cost products (i.e., high *PCH*) being overcosted and low-cost products (i.e., low *PCH*) being undercosted. However, the true, empirically unobservable benchmark product costs *PCB* decrease with an increasing overcosting (i.e, higher *PE*), highlighting the distortion caused by the costing system that affects product-based planning. I argue that the examined mechanism can explain this. Panel C of Table 22 shows a positive correlation between the reported product costs *PCH* and the directed specification error *SE*. Because overcosting occurs when there is a positive directed specification error in the resource consumption of a product, products with higher measured resource consumption (and higher reported product costs) have a higher probability of being overcosted. Consequently, if a costing system focuses on specific resource consumption, which is affected by an observable product characteristic, to allocate costs, products with a high specification of that characteristic have a higher probability of being overcosted. For instance, if indirect costs are only allocated via direct machine hours (i.e., a unit-level cost driver), products with a large fraction of direct machine hours (i.e., high-volume products) will receive an exceeding amount of costs (positive directed specification error) and are likely overcosted compared to products that require few direct machine hours. The applied modeling approach separates unit-level and non-unit-level resource consumption and costs, similar to prior studies (Balakrishnan et al., 2011; Schmidt et al., 2023). Hence, I expect that when a costing system only measures unit-level resource consumption, products with high (low) production volumes are overcosted (undercosted). In costing systems that only measure non-unit-level consumption, the opposite effect arises. I frame such costing systems as *one-tier costing systems* because they only consider one tier of resource consumption. Figure 34 illustrates that the numerical experiment supports the assumption that this is a consequence of the specified mechanism. The product-level errors increase with an increasing focus on one tier of resources to be employed as cost drivers (i.e., outer sections of the x-axis in Figure 34). In the example of Figure 34, high-volume products[68] are overcosted by one-tier costing systems with (mostly) only unit-level cost drivers because the costing system overemphasizes high resource consumption in unit-level resources (i.e., volume-related resources).

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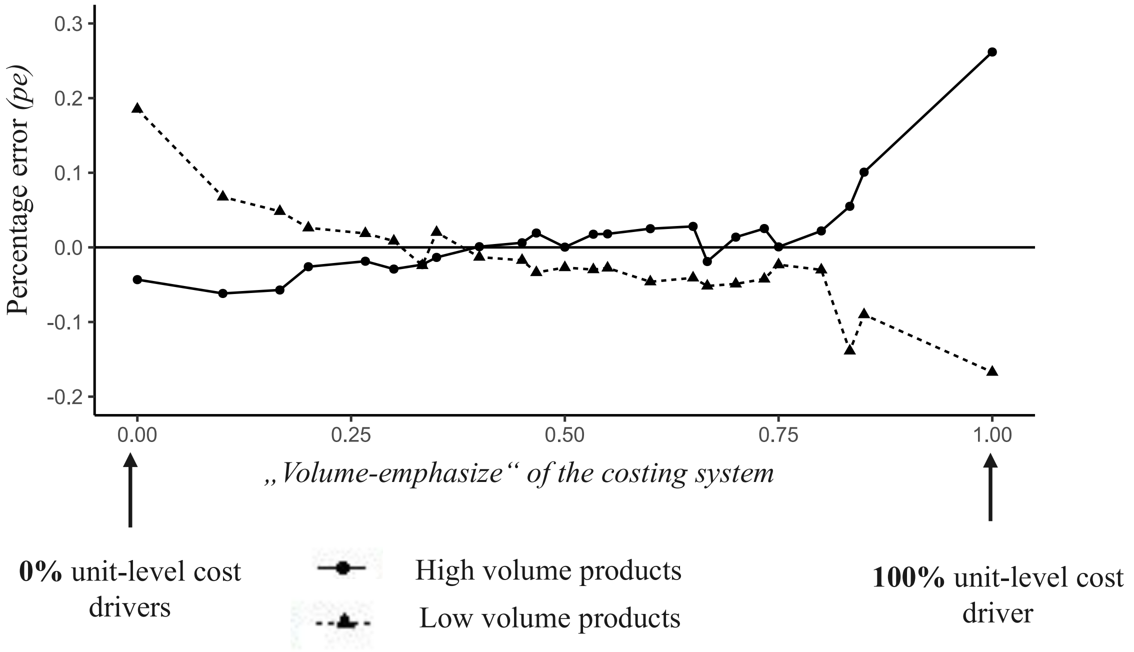
[68] I define products that have above median production volumes as “High volume” and products with below median production volume as “Low volume”.

Figure 34. The effect of one-tier costing systems on product-level errors in different products



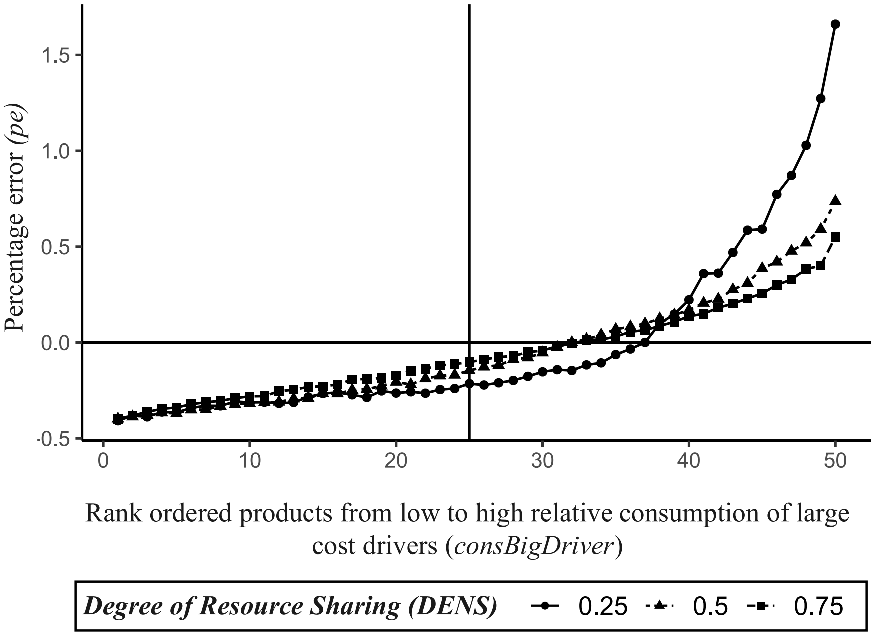
Overall, understanding what resources are employed as cost drivers helps identify large specification errors and which products are likely under- or overcosted. In that regard, the results emphasize the inferiority of so-called one-tier costing systems that focus only on specific areas of a firm's resource consumption.

As an additional challenge, knowledge about different tiers of resource consumption is difficult to obtain (Schmidt et al., 2023). A firm usually has no direct information about underlying resource consumption beyond the costing system (Labro & Vanhoucke, 2007). Instead, information taken from the costing system may be easily accessible and provides valuable information about a product's probability of being under- or overcosted.

The characteristics I derive are the fraction of consumed cost drivers from all cost drivers (*NumbDriver*) and the relative usage of cost-wise large cost drivers (*consBigDriver*). The results indicate that (highly) overcosted products consume a higher share of available cost drivers and larger magnitudes of large cost drivers. Especially *consBigDriver* correlates significantly with the product-level error (*PE*) (see Table 22). I understand that a high value for *consBigDriver* refers to a higher relative resource consumption that is measured instead of a potentially lower resource consumption that is not measured. As a result, the selected cost driver rate overstates the true percentage of a product's resource consumption, which results in a positive specification error.

When rank-ordering the products in the portfolio along their relative consumption of cost-wise large cost drivers, I observe an asymmetric effect between over-and undercosting (see Figure 35).

Figure 35. Rank-ordered products along consBigDriver



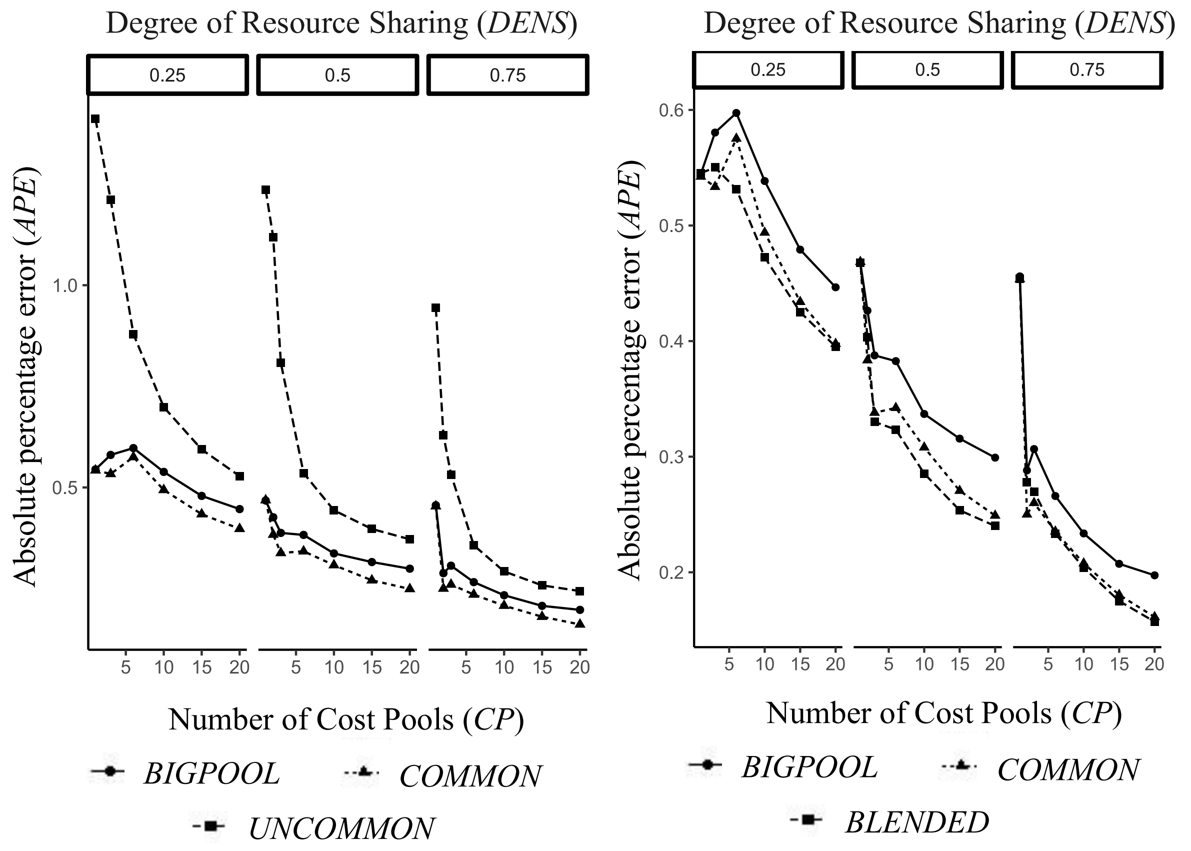
Largely overcosted products contain a much higher product-level error compared to undercosted products. In contrast, the majority of products are undercosted. A higher degree of resource sharing reduces this effect as resource consumption becomes more evenly distributed among products. These observations align with the findings from Labro and Vanhoucke (2007) and Table 21 that overcosted products contain a larger error. Nevertheless, overcosted products might be detectable using the relative usage of cost-wise large cost drivers as an indicator.

To summarize, especially the observable product characteristics sum of allocated costs (*PCH*), production volumes (*ProductVol*), and relative usage of cost-wise large cost drivers (*consBigDriver*) are strongly positively related to a product's overcosting. Although these three characteristics are based on the same mechanism, they are independent measures providing relevant product-based planning information. For instance, a product can be produced in medium quantities but consume a large amount of a high-cost cost driver. Therefore, the latter can serve as an additional indicator for the product-level error.

6.4.4 Deriving a Design Heuristic to Reduce Product-Level Errors

The examined mechanism and the characteristics of over- and undercosted products show that specification error is the main driver of large product-level errors. Interestingly, the results show that product-level errors are highest in production environments with low degrees of resource sharing (e.g., see Figure 30, Figure 35, and Table 21). This is also described in the pattern RC4 from Table 4. Consequently, high specification errors occur either if the selected cost driver percentage wrongly allocates zero percent of a particular resource's costs (undercosting) although the product consumes a particular resource's costs *or* if the selected cost driver percentage wrongly allocates a non-zero percentage of costs although the product does not consume a particular resource's costs (overcosting). Both cases are more likely in less dense resource consumption patterns. In this context, a costing system designer may be guided to focus on selecting cost drivers that either minimize or maximize zero entries in the cost driver rates. I operationalize this assumption by developing the two heuristics, "*COMMON*" and "*UNCOMMON*", that select the resource within a cost pool as the cost driver that has the least (*COMMON*) or most (*UNCOMMON*) zero-entries. In other words, the heuristic selects the most common or uncommon resource within a cost pool as its cost driver. Panel A of Figure 36 compares these two heuristics to the *BIGPOOL* heuristic. Interestingly, the *UNCOMMON* heuristic performs significantly worse than the *BIGPOOL* heuristic, while the *COMMON* heuristic performs most accurately. From the logic of the methods, the *UNCOMMON* method should have a high error from understating a non-zero entry with a zero entry in the cost driver percentage. The *BIGPOOL* method reduces this error, but since it still has a higher absolute percentage error than the *COMMON* method, the error from understating a non-zero entry in a product's resource consumption is larger than the error from overstating a zero entry with a non-zero entry in the cost driver percentage. This asymmetry in the cost allocation error results in the dominant undercosting pattern (CSB3, Table 4) in the modeled costing system with a *BIGPOOL* driver. The *COMMON* heuristic reduces this error further and exerts the lowest errors in product costs. The approach of the *COMMON* heuristic differs from the *BIGPOOL* heuristic as it does not follow the "*go where the money is"* approach for selecting cost drivers (Balakrishnan et al., 2011; Kaplan & Cooper, 1998b; Labro, 2019). Instead, it orientates on the resource consumption patterns to reduce specification errors, similar to the cost pooling heuristics (see Chapter 4).

Figure 36. Comparison between the heuristics *BIGPOOL*, *COMMON*, and *UNCOMMON*



Panel A: *COMMON* vs *UNCOMMON* vs *BIGPOOL*

Panel B: *COMMON* vs *BLENDED* vs *BIGPOOL*

Note. *BIGPOOL* selects the resource with the highest costs within a cost pool as the cost driver. *COMMON* selects the resource with the least zero entries in resource consumption as the cost driver. *UNCOMMON* selects the resource with the most zero entries in resource consumption as the cost driver. *BLENDED* selects a resource as a cost pool's cost driver if the resource's costs account for more than 20% of the cost pool's costs. The heuristic proceeds as the COMMON method if no such large resource exists within a cost pool.

I argue that the *COMMON* heuristic's information demand is similar to the one from *BIGPOOL* because a costing system designer only requires knowledge about more or less commonly used resources or activities in their firm's operations. Hence, the *COMMON* heuristic outperforms the *BIGPOOL* heuristic without necessarily requiring more implementation efforts. Conversely, in settings where resource costs are disparately distributed among resources, selecting cost-wise (very) large resources as the cost driver could be more accurate than the *COMMON* method. I therefore construct the *BLENDED* method, which combines *BIGPOOL* and *COMMON*. More precisely, *BLENDED* selects a resource as a cost pool's cost driver if the resource's costs account for more than 20% of the cost pool's costs. Suppose there is no such large resource within a cost pool; the heuristic proceeds as the *COMMON* method. Panel B of Figure 36 shows that the *BLENDED* method provides more accurate cost information than *BIGPOOL* and

COMMON and performs especially well in low degrees of resource-sharing settings. In the context of pattern RC4 (Table 4), which states that a low degree of resource sharing decreases the accuracy of cost allocation, this method can provide a valuable remedy to high errors in product costs.

6.5 ADDITIONAL ANALYSIS: CASE STUDY

To corroborate the results from the numerical experiment, I extend the investigation to a case study of a valve manufacturer. I obtain the cost driver rates from the manufacturer's costing system. The costing system consists of 23 unique drivers allocating costs to 150 different products. Of the 23 cost drivers, 17 (73%) are unit-level cost drivers and describe costs arising from using different production machinery that are not directly traceable to single variants and are therefore allocated via unit-level cost drivers. The remaining six cost drivers combine different support activities such as stock, operations, and logistics and are identified as non-unit-level cost drivers.[69] As I was only provided the cost driver rates and no information about production volumes and resource costs, I apply the simulation approach to the cost driver rates. More specifically, I treat the 23 cost driver rates as the resource consumption matrix (*RES_CONS_PAT*), on which I apply the costing system modeling as in the numerical experiments with fewer cost pools and cost drivers. To obtain a similar relation between resources and cost pools as in the numerical experiment (Table 20) I set the number of cost pools to 1,2,4,6,8,10. I leave the model unchanged and re-run the experiment with the implemented cost driver rates as the *RES_CONS_PAT*. This enables me to engage in a quasi-empirical setting that leverages the characteristics of an empirical costing system and employs more simulation runs to achieve greater robustness.

Generally, I find the results from the numerical experiment corroborated in the quasi-empirical case study. Table 23 and Table 24 report similar relations for the descriptive statistics compared to the numerical experiment (Table 21 and Table 22). Due to the given resource consumption matrix, the degree of resource sharing is fixed. I observe the expected decreasing system-level error with increasing disaggregation for the number of cost pools. Again, the mean absolute percentage error (*MAPE*) is higher for overcosted products than undercosted ones. Also, the concentration of the share of system-level error caused by the top 10% of products with the highest error is similar to the numerical experiment and remains at around 30%. In contrast to the numerical experiment, cost allocation based on the case study resource consumption results

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[69] Table 30 in the appendix of this paper overviews the different cost drivers from the manufacturer's costing system.

in a dominant overcosting, where most materially falsely costed products are overcosted instead of undercosted. This also counters the results from the numerical experiment in Labro and Vanhoucke (2007) that report a dominant undercosting. Hence, these results indicate exceptions to this pattern (CSB3; Table 4) exist.

Table 23. Case study: Descriptive statistics of system-level error measures

Panel A: Degree of Resource Sharing

Density of resource consumption matrix (*DENS*)	Units	Global Average
System-level Error (*EUCD*)	€	334717
Share of accurately costed products (*%ACC*)	Percent	0.16
MAPE of overcosted products	Percent	0.35
MAPE of undercosted products	Percent	0.26
Percentage of *EUCD* caused by top 10% products (*ErrorDisp*)	Percent	0.30
Share of undercosted products (*UCShare*)	Percent	0.45

Panel B: Number of Cost Pools

Refinement of Costing System (Number of Cost Pools, CP)	Units	Global Average	Single-Cost Pool (CP = 1)	Medium number of Cost Pools (CP = 4)	High number of Cost Pools (CP = 10)
System-level Error (*EUCD*)	€	334717	597020	304525	126847
Share of accurately costed products (*%ACC*)	Percent	0.16	0.05	0.13	0.29
MAPE of overcosted products	Percent	0.35	0.60	0.29	0.12
MAPE of undercosted products	Percent	0.26	0.46	0.23	0.11
Percentage of *EUCD* caused by top 10% products (*ErrorDisp*)	Percent	0.30	0.28	0.31	0.29
Share of undercosted products (*UCShare*)	Percent	0.45	0.55	0.44	0.41

Note. *CP* = Number of cost pools; *DENS* = Degree of resource sharing (which equals 0.7 in the case study).

Table 24. Case Study: Overview of characteristics of under- and overcosted products

Panel A: Single Product Characteristics

	Units	Min	Quartile 1	Median	Mean	Quartile 3	Max
ProductVol	Number	1	3	5	7.17	8	474
NumbRes	Number	12	15	16	16.03	17	19
PCB	€	255	627	933	2209	1748	187132
PCH	€	3	642	941	2061	1582	344899
NumbDriver	Number	0.25	0.75	0.88	0.86	1.00	1.00
consBigDriver	Percent	0.00	0.00	0.01	0.01	0.01	0.50

Panel B: Characteristics of under- and overcosted products (average values)

	Units	Global Average	Highly Undercosted (*PE* < -20%)	Undercosted (*PE* < -5%)	No Error	Overcosted (*PE* > 5%)	Highly Overcosted (*PE* > 20%)
ProductVol	Number	7.00	6.90	6.93	7.47	8.10	7.40
NumbRes	Number	16	16	16	16	16	16
PCB	€	2209	3421	2820	1947	1795	1890
PCH	€	2061	1232	1464	1946	2593	3152
NumbDriver	Percent	0.85	0.83	0.82	0.89	0.93	0.86
consBigDriver	Percent	0.01	0.00	0.00	0.01	0.02	0.01

Panel C: Pearson-Correlation of product characteristics and product-level error[1]

	ProductVol	*NumbRespch*		*NumbDriver*	*consBig Driver*	*AE*	*SE*	*PE*
ProductVol	1	0.21	-0.09	-0.03	0.62	0.00	0.40	0.06
NumbRes		1	0.01	0.20	0.15	0.00	0.10	-0.01
PCH			1	0.08	0.46	-0.01	0.20	0.17
NumbDriver				1	0.06	0.18	0.03	0.24
consBigDriver					1	0.00	0.49	0.24
AE						1	-0.14	0.00
SE							1	0.25
PE								1

Note. *ProductVol* = Production volume of a product; *NumbRes* = Number of consumed resources; *PCB* = Benchmark product costs; *PCH* = Reported product costs; *NumbDriver*; Fraction of available cost drivers; *consBigDriver* = Relative usage of cost-wise large cost drivers. *AE* = Aggregation error; *SE* = *Directed* specification error; *PE* = Percentage error. [1]All correlations are significant at $p<0.05$.

Concerning product characteristics that determine overcosted and undercosted products, the case study generally corroborates the results from the numerical experiment. More specifically, (highly) overcosted products receive a greater amount of overhead costs (*PCH*), consume a larger fraction of available cost drivers (*NumbDriver*), and a relatively higher share of large cost drivers (*consBigDriver*). However, the production volume of a product (*ProductVol*) and the number of consumed resources (*NumbRes*) vary only marginally with a product's probability for over- or undercosting. In general, although the results support the findings from the numerical experiment, they are less pronounced. I understand that due to the high ratio of products to resources (i.e., 150 products to 23 resources), the resource consumption among all products is relatively homogeneous compared to the resource consumption in the numerical experiment (i.e., 50 products to 50 resources), resulting in less pronounced relations between product characteristics and product-level errors. Panel C of Table 24 indicates a high correlation between percentage error *PE*, specification error *SE*, and the relative consumption of large cost drivers *consBigDriver*. This further substantiates that the examined mechanism also occurs in the empirically derived resource consumption. In summary, the case study enables leverage of the pure numerical experiment toward greater structural realism (Grimm et al., 2005) and validates the corresponding results.

6.6 CONCLUSION

The objective of the analysis in this chapter is to provide a better understanding of how costing systems distort the costs of single products. I first descriptively scrutinize the errors in single products (product-level error) as opposed to the overall error of a portfolio (system-level error). The results show that the system-level error distributes unevenly along single products, posing a challenge for product-based planning with certain products containing relatively large product-level errors. Next, I investigate the precise mechanism behind product-level errors and over- and undercosting by measuring each product's aggregation and specification errors. I find that the aggregation error does not directly drive the product-level error but increases the probability for a high specification error, which manifests a product-level error.

To provide practical guidance, I investigate whether over- or undercosted products have distinct observable characteristics that may signal the corresponding error. The numerical experiment tests five observable product characteristics that influence the resource consumption of a product and potentially indicate a higher likelihood of over- or undercosting. From the tested product characteristics, higher values for the production volume of a product, the sum of allocated costs, and the relative consumption of large cost drivers generally signal a higher probability for a product to be overcosted. The number of consumed resources and the number of used cost drivers indicate a similar yet weaker relation with the product-level error. Lastly, I derive two novel costing system design heuristics that provide more accurate product costs than the widely shared *BIGPOOL* heuristic.

The results contribute to literature and practice in several ways. First, the findings contribute to the cost accounting literature (Horngren et al., 2015; Labro, 2019), by providing descriptive evidence on how errors in reported costs are distributed among single products in the portfolio. Hence, I illustrate the importance of this detailed perspective on product-level errors for product-based planning and similarly address corresponding cross-subsidization patterns in cost accounting (see Table 4).

Second, I provide practically applicable guidelines. I show how different product characteristics in combination with costing system design can signal detrimental product-level errors. This may help managers reduce sub-optimal product-based planning decisions without re-designing their costing system (Dierynck & Labro, 2018b). In that regard, the findings show how information from the costing system usage can enable insights into cost allocation errors (Mastilak, 2011). In particular, firms can be advised to exploit this potentially priorly unused data source for their cost accounting. Additionally, I develop two novel and information-effective costing system design heuristics (*COMMON* and *BLENDED*) that can guide practice. Finally, the investigation adds to the literature on costing system design specifically, as the results provide further insights into the mechanism behind product-level errors (Labro & Vanhoucke, 2007, 2008). To be precise, I update the relationship between aggregation and specification errors as I show that the aggregation error only indirectly increases the error in product costs, mediated by the specification error. Based on this, I stress the inferiority of one-tier costing systems with the highest specification errors. Methodologically, the approach showcases how empirical costing systems can be enriched with numerical experiments to increase the structural realism of a simulation model and the validity of its results (Grimm et al., 2005). This can guide future research on errors in product cost information.

Lastly, this analysis has limitations that may provide areas for future research. First, I acknowledge the limited external validity of simplified simulation models and numerical experiments (Balakrishnan & Penno, 2014) and call for further empirical research to test the applicability of the results concerning product-level determinants (e.g., in case studies as suggested). Second, I understand the scope of the simulation model employed here and expect that potentially even more relevant product-level determinants exist that are currently not incorporated into the model.

7 OVERALL CONCLUSION AND DISCUSSION

7.1 REVISITING THE PATTERNS OF ERRORS IN PRODUCT COST INFORMATION

The main objective of this thesis was to investigate errors in product cost information caused by product costing systems and to extend the current understanding of this process. Table 4 summarized currently known and observed recurring patterns of errors in cost information. These patterns display the current notions of how errors in product cost information arise and manifest in different products' costs. The challenge arises as the patterns in Table 4 are based on difficult-to-compare studies from either numerical, empirical, or textbook-based backgrounds, challenging the validity of corresponding notions (Shields, 2015). To address this, this thesis replicated and extended two simulation models to test the reproducibility and boundary conditions of identified patterns in Table 4 in large-scale numerical experiments. The summarized results are shown in Table 25.

Table 25. Findings on patterns of errors in cost information

Abbre-viation	Name	Description	Summarized Findings
Costing System Design			
CSD1	Cost Pool Relationship	*A greater number of cost pools decreases the system-level error.*	Generally reproduced. However, Figure 16 and Figure 14 show that increasing the number of cost pools from a single-cost pool costing system can reduce the accuracy. Offsetting effects must be considered when increasing the number of cost pools. Additionally, the mechanism analysis of product-level errors (Figure 29) shows that the number of cost pools does not linearly decrease the aggregation and specification errors.
CSD2	Driver Sophistication	*A higher sophistication of cost drivers decreases the system-level error.*	Generally reproduced. However, one cost driver only allocates the costs of a single cost pool. Thus, when resource consumption is segregated into several tiers, simple cost drivers from different tiers of resources may outperform information-demanding cost drivers from only one tier (Figure 34).
CSD3	Willie-Sutton Rule	*A higher share of direct costs decreases the system-level error.*	Not addressed.

Table 25 (continued).

CSD4	ABC > VBC	*ABC computes more accurate product costs than VBC.*	ABC employs multiple cost drivers from different tiers of resource consumption. This generally aids the accuracy of a costing system. However, when costs are only caused by unit-level resources, VBC can result in accurate product costs and requires fewer implementation efforts (Figure 20).
Resource Consumption			
RC1	Heterogeneity Effect	*Higher heterogeneity in resource consumption generally increases system-level errors.*	Heterogeneity in resource consumption is a multifaceted construct. Generally, more heterogeneous resource consumption impedes accurate cost allocation (e.g., see Figure 11, Figure 12 and Figure 13). However, heterogeneity can also provide more information and structure, which can be employed by certain costing systems to reduce errors in costs (Figure 14). Additionally, heterogeneity can increase offsetting effects in errors (Figure 14), which benefits very simple costing systems in particular.
RC2	Production Quantity Effect	*A greater dissimilarity in production quantities between products increases system-level errors.*	Generally reproduced. Greater dissimilarity in production quantities results in less homogeneous resource consumption of volume-related resources (e.g., unit-level). This increases product cost cross-subsidization (Table 19), product-level errors (Table 22), and system-level errors.
RC3	Correlation Effect	*A lower correlation in resource consumption increases system-level errors.*	Generally reproduced. Lower correlations between different resources' consumption patterns make it more random and less structured. This generally impedes cost allocation and increases the system-level error (Table 8). Additionally, it results in larger aggregation errors, which drive specification and product-level errors (Figure 31).
RC4	Degree of Resource Sharing	*A lower degree of resource sharing increases system-level errors.*	Generally reproduced (e.g., Figure 17). However, a lower degree of resource sharing can benefit cost tracing, which increases the direct cost share and thus results in fewer costs to be allocated via the costing system (CSD3).
RC5	Time Effect	*Resource consumption changes and increases system-level errors over time.*	Not addressed.

Table 25 (continued).

Cross-Subsidization

CSB1	VBC Volume-bias	*VBC systems undercost low-volume products and overcost high volume products.*	This only occurs when resources are not consumed in direct correlation with production volume (Figure 22). If an ABC system also allocates costs only via one tier of resource consumption, this pattern can also occur (Figure 34).
CSB2	VBC Individuality-bias	*VBC systems undercost individualized products and overcost standard products.*	Not reproduced. Based on the number of different resources consumed to measure individuality, this pattern could not be reproduced (Table 22). Instead, Chapter 6 suggests that individualized products are produced in lower quantities and have a higher share of non-unit-level costs. These characteristics result in an undercosting of individualized products (Table 22).
CSB3	Dominant Undercosting	*In ABC systems more products are being under- than overcosted.*	Generally reproduced in the conducted numerical experiments (see Table 16 and Table 21). However, in the applied case study in Chapter 6, the pattern switches to a dominant overcosting pattern (Table 23).

The simulation-based analysis of this thesis did not address patterns CSD3 (Willie-Sutton-Rule) and RC5 (Time effect) because it solely focused on the allocation of indirect costs in a static non-longitudinal costing system. Mertens (2020) and Anand et al. (2014) take these two aspects into their consideration. Apart from these patterns, the relations described in the majority of patterns are generally reproduced. However, several limitations and boundary conditions relevant to costing system design and cost-based decision-making are identified and described. Regarding the overall objective of expanding the understanding of errors in cost information, two major themes emerged from the results. First, the results show that offsetting effects of errors appear more prevalent than previously observed. This affects several of the above patterns. Due to this effect, more cost pools and more information-demanding cost drivers (CSD1 and CSD2) only seldom improve accuracy when refining very simple costing systems to subsequent medium simple costing systems. Additionally, higher heterogeneity (RC1) and lower correlations (RC3), which cause these offsetting effects, do not always result in higher errors. Overall, since these effects are caused by a cost hierarchy derived in high alignment with empirical observations and theoretical predictions, it can be argued that in empirical costing systems, the offsetting effects of errors are also higher than in prior simulation studies. This is highly relevant for costing system designers as simple refinements will not pay off in higher accuracy in many scenarios, which refines prior believes (Labro & Vanhoucke, 2007). The results also specify more settings where offsetting occurs and reduce potential ambiguities of the priorly sparse literature on offsetting effects (Datar & Gupta, 1994).

The second theme centers around the specification of resource consumption patterns and their influence on errors in product cost information. More precisely, the mechanisms behind product cost errors are examined by disentangling resource consumption in greater detail. This addresses especially the patterns in the product cost cross-subsidization category. First, the VBC volume-bias (CSB1) mechanism has been examined and related to the presence of non-unit-level costs and a volume-based costing system. Based on this, Chapter 6 shows that the VBC individuality-bias’ (CSB2) driving force appears to be a product's production volumes instead of its individuality. Additionally, Chapter 6 examines the general mechanism behind errors in product costs of single products. The results show how different characteristics of resource consumption and costing system design result in aggregation and specification errors that, in turn, manifest errors in product costs. Accordingly, the results link the error types and the system's characteristics (i.e., resource consumption and costing system design, Figure 3) more closely. Prior research either modeled error types (Labro & Vanhoucke, 2007) or different production environments and costing systems without investigating the resulting error types (Balakrishnan et al., 2011). Overall, this thesis adds to the interlinking between the different patterns and emphasizes that they should not be considered standalone relations but part of a complex system interacting with each other. For instance, by showing that the aggregation error does not directly affect the errors in product costs, increasing the number of cost pools and decreasing the aggregation error (CSD1) is only worthwhile if appropriate cost drivers are selected (CSD2). Another example may be that the potential superiority of ABC over VBC (CSD4) requires sufficient heterogeneity in non-unit-level resource consumption (RC1), which is displayed by correlations of consumption patterns (RC4) and degree of resource sharing (RC3). Conversely, greater disparity in production volumes (RC2) may favor VBC systems if only unit-level costs are present in a firm's resource consumption.

To summarize, although these results stress the interactions between patterns of errors in cost information and the errors within a costing system, they aim to provide an updated and expanded understanding of cost allocation and resulting errors in product cost information.

7.2 LIMITATIONS OF THE CURRENT MODELING OF COSTING SYSTEMS

The main methodology employed in this thesis is modeling and simulation because it allows the assessment of errors in reported product cost information in various scenarios, such as different costing system designs or production environments (Labro, 2015). Due to these reasons, simulation modeling emerged as a central approach in the literature on errors in product cost information (Labro, 2019). This literature provided two main simulation models. First, the simulation model from Balakrishnan et al. (2011) (short BHL), which has been replicated and extended in Chapter 4, and the simulation model from Anand et al. (2019) (short ABL), which has been replicated and extended in Chapter 5 of this thesis. Despite the rigorous testing through replication and extension and the corresponding assessment and comparison of produced results with prior observations (Table 25), several limitations within these models prevail. These limitations may arise from (un-)intentional design choices to reduce complexity (Robinson, 2008a) or constraints caused by the implementation into a software environment. Reducing these prevailing limitations through extensions or robustness analyses (such as in the case of the ABC cost hierarchy in this thesis) may open up new perspectives and insights into errors in product cost information.

The most named limitation of the current simulation models is the assumption of linearity in resource and cost consumption (Labro, 2019). Contrarily, due to economies of scale or scope (Fixson, 2006) , managerial action (Banker & Byzalov, 2014) or other influences (Labro, 2019) cost behavior and resource consumption are often non-linear (Christensen, 2010). Implementing such cost behavior into a modeling approach may show its effects on costing system design and errors in cost information, which can affect design rules or patterns of errors in cost information. Regarding nonlinearity, the current models only observe static snapshots of resource consumption without a timely perspective. Thus, questions arise about how costing systems should treat costs committed in prior periods or how costing systems should be adjusted to accommodate new consumption patterns or new products (Anand et al., 2014). This perspective also includes the differentiation between fixed and variable costs beyond their effect on consumption patterns.

A more technical limitation of the current modeling is the assumption of a “base” resource, which is the cost-wise largest resource (in ABL) and consumed by every product. Due to this modeling aspect, selecting this base resource as a cost driver significantly reduces the system-level error. However, whether such a major resource is generally present in empirical resource consumption patterns remains unclear. If there are single large costs connected to only one resource or activity, it rather appears worthwhile to trace the costs of such resources directly to single products instead of allocating them via the costing system (Kerremans et al., 1991).

Next, both models employ the consumption patterns of single resources as the cost drivers of the costing system. Hence, resources from all tiers of the cost hierarchy can be employed as cost drivers, which is generally the main innovation of ABC (Balakrishnan et al., 2011). In contrast, the modeled resource consumption for the volume-based costing system in Chapter 5 employs the production volumes of a product as the cost driver. In other words, the cost driver is not a direct consumption pattern of a resource but a related yet different measure. This also seems likely in practice, where driver rates are constructed and do not reflect the exact consumption of a resource. For example, maintenance costs of different machinery may be allocated to products via a cost driver based on the number of maintenance personnel. Thus, the cost driver is only a measurable approximation of actual resource consumption. The modeling lacks this additional dimension and hence employs resources as cost drivers. An adjustment of the modeling to include this "driver-dimension" potentially affects specification and measurement errors of the costing system. Additionally, potential new costing system design rules can be developed that address the construction of approximative measures as cost drivers. As a partial remedy, the current models introduce measurement errors to the cost drivers, which ought to mirror the difference between resource consumption and cost drivers. However, the measurement error is currently generated completely randomly and hence does not affect the systematic error (i.e., bias) in reported product costs but instead generates noise around true costs (Mertens & Meyer, 2020). Due to the static snapshot characteristic of the current models, the effect of noise in reported product costs has not received much attention as the results were found to be intuitive (Balakrishnan et al., 2011). However, this may change when observing product cost errors over time or when using them for product-based planning (Mertens & Meyer, 2020). Additionally, empirical studies on measurement errors found that they are, in fact, not purely random (Cardinaels & Labro, 2008; Schuhmacher & Burkert, 2021). Thus, it seems worthwhile to investigate more closely where measurement errors arise in the cost allocation process and what their characteristics are. An additional "driver-dimension" may be a helpful starting point.

Lastly, a general limitation is the validity of the overall resource consumption pattern as generated by the models. Although this thesis has already developed and tested different resource consumption patterns through different cost hierarchies derived from empiricism, several limitations still exist. For instance, the relationship between different products' design and their consumption of indirect costs is still unclear (Labro, 2004). Many engineering studies investigate how different product design approaches (e.g., modularity) affect direct resource consumption patterns, such as the re-usability and commonality of components (Israelsen & Jørgensen, 2011; Mertens et al., 2021). However, how such decisions affect indirect resource consumption remains unclear. This also includes complexity costs (Myrodia et al., 2021), which are considered difficult to measure and to allocate to single products. Empirical investigations about how such effects shape resource consumption and the implementation of emerging patterns can benefit the validity of the models' results and findings.

The current models only employ the degree of resource sharing (Balakrishnan et al., 2011) as an approximation to different production environments. However, this degree of resource sharing is randomly generated and spread over the resource consumption matrix, although different products and tiers in the cost hierarchy may be affected differently. For example, facility-sustaining costs may be shared more evenly between products and thus have lower resource sharing than unit-level costs. Consequently, a more specified application of the degree of resource sharing in the resource consumption matrix can be a good starting point to improve the current modeling.

Overall, the modeling in this thesis and prior studies already set a solid foundation for investigating errors in product cost information, which, however, can be further improved as elaborated above. Modeling strategies, such as pattern-oriented modeling (Grimm et al., 2005) or a stylized-facts-based approach (Meyer, 2019) can support and guide this development. More specifically, research on cost allocation can be connected to neighboring research fields, such as engineering design, product-mix decisions, or capacity planning (Anand et al., 2023; Davila & Wouters, 2004). From these fields, patterns potentially related to cost information errors can be extracted and examined in more detail. A prominent example of this may be the cost-based death spiral, where firms drop seemingly unprofitable products because the provided product cost information is distorted (Dierynck & Labro, 2018b). Although this pattern is widely recognized (Bloomfield, 2016), its characteristics have not yet been examined apart from smaller numerical examples or limited case studies and linked to errors caused by the costing system.

7.3 CONCLUSION AND SUMMARY

This thesis aims to expand the current understanding of how costing systems cause errors in product cost information. This included several steps and resulted in different contributions from several results within this thesis. Along with the main objectives (see Chapter 1) the following contributions are summarized.

[1] Patterns of errors in product cost information

The existing field of research was overviewed, and several recurring observations in the form of patterns of errors in cost information were listed. More specifically, I identified four patterns regarding the effect of costing system design on errors in product cost information, five on the effect of resource consumption on errors in product cost information, and three on product-level errors and product cost cross-subsidization. Although the list is not exhaustive, it aids in connecting a *“mile wide and an inch deep*” (Shields, 2015, p. 129) field of research. The resulting classification of corresponding references highlighted the scientific base of each pattern. Based on this, I summarize and assign key findings to each pattern to underline potential limitations or validity concerns. Overall, this may guide practitioners in understanding the effects of costing system design and resource consumption on errors in product cost information and cross-subsidization and can aid future research endeavors.

[2] Internal validity of simulation models through model replication

Two prominent simulation models in the field of cost accounting from Anand et al. (2019) and Balakrishnan et al. (2011) were replicated following best practices in model replication approaches (Wilensky & Rand, 2007). The replications provided insights into the internal validity of the models and corresponding results. They showed that the majority of findings are internally valid but also identified several boundary conditions and limitations. This contributes to the evaluation of these results and their practical implications. Additionally, by conducting the two model replications, this thesis contributes to the overall discussion of replicability in accounting (Hail et al., 2020) and of simulation models (Thiele & Grimm, 2015). The approaches that have been conducted can be an additional blueprint for future model replication studies.

[3] External validity of findings toward an ABC cost hierarchy

Since costing systems are required to reflect underlying resource consumption accurately to reduce errors in reported cost information, the assumed characteristics and structure of resource consumption are decisive for the design of the costing system and the derived design rules (Balakrishnan et al., 2011). The ABC cost hierarchy is a widely discussed concept for how resource consumption is structured and had a great influence on the design of costing systems (Horngren et al., 2015). By implementing an ABC cost hierarchy into both replicated models’ resource consumption, I scrutinized the external validity of results toward this change. Especially regarding costing system design heuristics, the results show that more information-demanding costing systems do not necessarily outperform very simple costing systems. This is due to increased offsetting effects and more structure in resource consumption caused by the ABC cost hierarchy. These findings contribute to costing system design practice and theory by addressing the typical trade-off between the costs of errors and the costs of costing system design and implementation (Cooper, 1989).

[4] Pattern of product cost cross-subsidization in VBC systems

This thesis adds to the better understanding of the pattern of product cost cross-subsidization in VBC systems. The pattern is among the most named patterns in costing system research and has been framed as a major reason for the development of ABC (Cooper & Kaplan, 1991). Contrarily, evidence of this pattern is limited to a few numerical examples or conceptualizations. This thesis, therefore, investigated the precise mechanism behind the pattern. The results indicate that volume-based cost drivers in pairing with non-unit-level costs are required to evoke the pattern. This may specify scenarios where the pattern is more or less likely to occur and therein aids costing system designers when potentially deciding between a volume-based or activity-based costing system and when to be cautious with provided cost information, making the findings practically relevant.

[5] Investigation of product-level errors

Product-level errors are potentially more important than system-level errors in cost-based decisions and product-based planning. Contrarily, prior research on product-level errors is scarce. In this thesis, I investigated product-level errors as opposed to system-level errors. I find that the system-level error is unevenly distributed among single products in the product portfolio, with few products containing large errors in their costs. This highlights the importance of product-specific costing errors compared to an average or sum of all errors in a product portfolio. Additionally, I observe that higher values for the production volume of a product, the sum of allocated costs, and the relative consumption of large cost drivers generally signal a higher probability for a product to be overcosted. I corroborated these observations by specifying the underlying mechanism that determines why and which products are over- or undercosted in a given costing system. Additionally, I developed two novel rules of thumb for costing system design, which perform more accurately than comparable established methods. Lastly, I apply the approach to a quasi-empirical case study that supports the findings. The provided insights not only update the knowledge about how errors in cost information are distributed along single products but also how these errors precisely emerge and how large errors can be identified or reduced with new costing system design heuristics. These findings contribute to product-based planning and cost-based decision-making by providing relevant managerial guidance.

Overall, this thesis started with the objective of providing an updated and expanded understanding of errors in product cost information. Offering an overview of the current patterns and resulting notions of errors in cost information, this thesis provides a solid stepping stone for further research endeavors and practical guidance. Employing this overview, I replicate and extend two prominent simulation models in the field of errors in cost information, thereby increasing both the internal and external validity of corresponding results, recommendations, and connected patterns. Throughout this testing, several results updated the understanding of mechanisms behind errors in product costs and provided new applicable heuristics and guidance. In summary, this thesis contributes to practice and literature by providing an overview of the functionality of costing systems and antecedents of errors, which can be used to identify new research opportunities, design effective costing systems, and guide managerial decision-making.

Lastly, the results do come with limitations. First, the technical limitations of the current modeling approaches of costing systems still limit the external validity of the results (see Chapter 7.2). Addressing the named and further aspects can provide fruitful avenues for future research on errors in product cost information using simulation modeling. Second, the results mainly center around antecedents of errors in cost information and do not focus on their consequences. Future studies should link errors in cost allocation with potential consequences in affected decision-making, thereby highlighting settings where cost information accuracy is most important. Lastly, empirical research on costing system design and resource consumption is sparse (Labro, 2019). More empirical research can provide descriptive evidence about the characteristics of how products consume resources and costs or by what rules firms design costing systems.

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9 APPENDIX

9.1 APPENDIX 1: EMPIRICAL OBSERVATIONS OF COSTING SYSTEM DESIGNS

Table 26. Empirical observations of costing system design

Reference	**Type of study and sample size**	**Selected findings regarding costing system Design choice**		
		Number of Cost Pools	Type of Cost Driver	Grouping Cost Pools
Drury and Tayles (1994)	Survey, UK Manufacturing firms; N = 260	• 26% of the firms used a single cost pool costing system.	• 91% of firms employed volume-based costing systems.	-
Innes and Mitchell (1995)	Survey, UK's largest firms, N= 251	-	• 19.5% employed ABC.	-
Bjørnenak (1997)	Survey, Norwegian Firms, N = 75	• Firms employed 1-2 allocation bases on average.	• 40% employed ABC.	-
(Clarke, Hill, & Stevens, 1999)	Survey, Irish Manufacturing firms, N = 204	•	• 12% employed ABC.	
Ittner, Lanen, and Larcker (2002)	Survey, US-based individual participants	-	• 26% used ABC *extensively*.	-
Cagwin and Bouwman (2002)	Survey, Participants from the Institute of Internal Auditors (IIA), N= 204	-	• 31% employed ABC.	-
(Drury & Tayles, 2005)	Survey, Chartered Management Accounting (CIMA) Members, N = 187	• 34% of firms employ a single allocation base.	-	-
Al-Omiri and Drury (2007)	Survey, UK firms; N= 176	• 30% of the firms used a single cost pool costing system.	• 35% employed volume-based costing systems. • 29 % employed ABC.	-

9.2 APPENDIX 2: COMPARISON BETWEEN ORIGINAL MODEL FROM BHL AND THE ABC COST HIERARCHY EXTENSION

Table 27. Comparison between the original model and ABC cost hierarchy extension

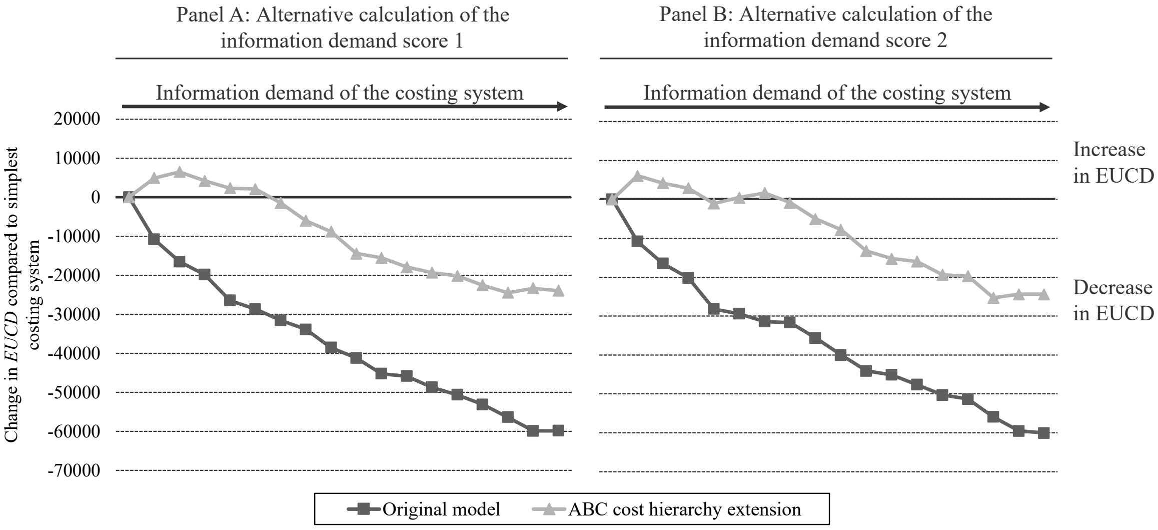
Parameter	**Original model/Close replication**	**ABC cost hierarchy extension**
Benchmark system		
Number of products	50	50
Number of resources	50	50
Number of tiers in cost hierarchy	2 (volume-level and batch-level)	4 (unit-level, batch-level, product-sustaining-level, facility-sustaining-level)
Separation of number of resources into tiers (number of entries in *RCC* and *RES_CONS_PAT* add up to the respective share of number of resources)	Volume-level: 50% Batch-level: 50%	Unit-level: 35% Batch-level: 46% Product-sustaining-level: 8.3% Facility-sustaining-level: 9.7%
Separation of costs into tiers (values in *RCC* add up to the respective share of total costs *TC*)	Volume-level: 50-80% Batch-level: 20-50%	Unit-level: 45% Batch-level: 19% Product-sustaining-level: 17% Facility-sustaining-level: 19%
Costing System		
Cost pool allocation heuristics	*Random* *Size-random* *Size-misc* *Correl-random* *Correl-misc* *Blended*	*Random* *Size-random* *Size-misc* *Correl-random* *Correl-misc* *Blended-updated*
Cost driver selection heuristics	*BIGPOOL* Num = 2 Num = 4 Num = 5 Average	*BIGPOOL* Num = 2 Num = 4 Num = 5 Average

Note. Changed parameters/heuristics between the original model and ABC cost hierarchy extension are highlighted in grey-shade.

9.3 APPENDIX 3: ALTERNATIVE CALCULATIONS FOR THE INFORMATION-DEMAND SCORE

To substantiate the robustness of the results depicted in Figure 14, I calculate two alternative information-demand scores and show that the qualitative results remain valid toward this change. Figure 37 shows the results for these two altered scores, while Table 28 reports the scores for each heuristic for the two additional calculations. For the first alternative calculation, I assume that grouping low-cost resources into a miscellaneous cost pool requires more information than distributing these resources over all cost pools. For the second alternative calculation, I assume that allocating resources to cost pools based on correlating resource consumption requires more information than size-based heuristics. Hence, I increase the information score for these heuristics. Adding more cost pools to the costing system still leads to a proportional increase in information demand (i.e., the number of cost pools equals the score).

Figure 37. Alternative calculations of the information-demand score



Note. *EUCD* = Euclidean Distance between benchmark and reported product costs for all products in the portfolio.

Table 28. Information-demand score for each heuristic for alternative calculations

Alternative calculation of information-demand score 1

CP-Heuristic	**Score**	**CD-Heuristic**	**Score**
Random	0	*BIGPOOL*	0
Size-random	1	*Num2*	1
Size-misc	2	*Num4*	2
Correlation-random	3	*Num5*	3
Correlation-size	4	*Average*	4
Blended	5		

Alternative calculation of information-demand score 2

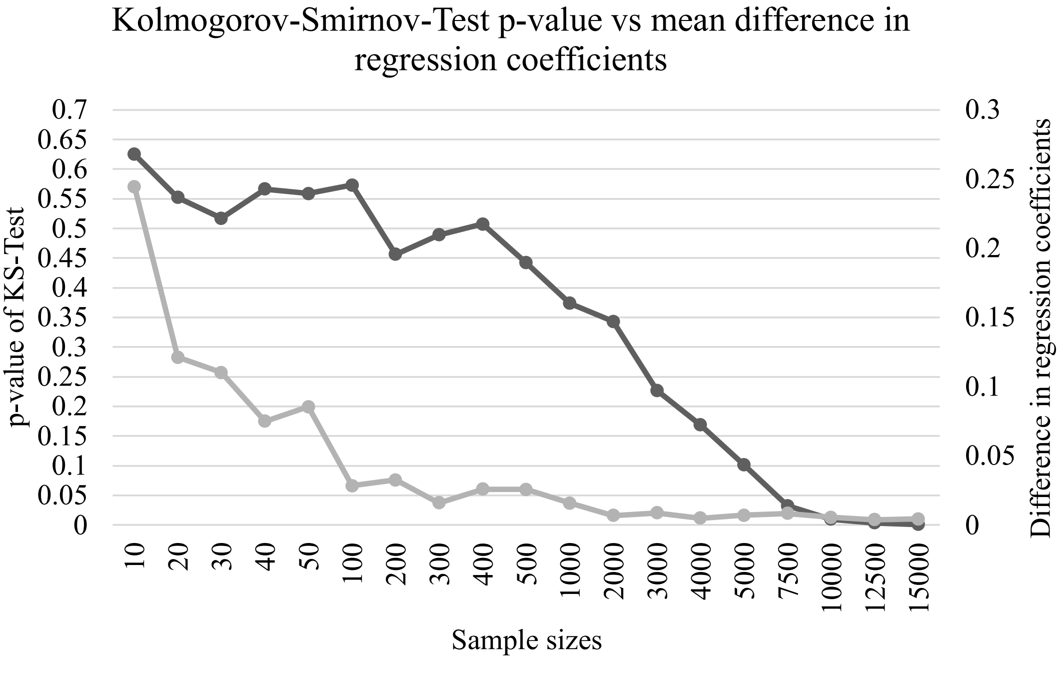
CP-Heuristic	**Score**	**CD-Heuristic**	**Score**
Random	0	*BIGPOOL*	0
Size-random	1	*Num2*	1
Size-misc	2	*Num4*	2
Correlation-random	4	*Num5*	3
Correlation-size	4	*Average*	4
Blended	5		

Note. I employed the *blended* method as described in BHL for the original model and the *blended- updated* method for the ABC cost hierarchy model.

9.4 APPENDIX 4: KOLMOGOROV-SMIRNOV-TEST DISTORTION FOR INCREASING SAMPLE SIZES[70]

I test whether the Kolmogorov-Smirnov-test is flawed toward increasing sample sizes. The figure illustrates that as the sample size increases, the mean difference between the regression coefficients of the original and replicated models diminishes. This leads to an augmentation of relational equivalence as the impacts of regression coefficients on the dependent variable (*MAPE*) become more aligned. In contrast, the p-value associated with the Kolmogorov-Smirnov Test decreases as sample sizes grow. A reduced p-value signifies substantial differences in distributional equivalence. This underscores the inadequacy of statistical significance tests, such as the Kolmogorov-Smirnov Test (KS-Test), for large sample sizes.

Figure 38. KS-Test p-value vs. mean difference in regression coefficients



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[70] This appendix is based on the corresponding appendix of Schmidt, M., Mertens, K. G., & Meyer, M. (2023). Cost hierarchies and the pattern of product cost cross-subsidization: extending a computational model of costing system design. *PLOS ONE, 18*(9). doi: 10.1371/journal.pone.0290370

9.5 APPENDIX 5: OVERVIEW OF VARIABLES AND TECHNICAL TERMS FOR THE MODEL IN CHAPTER 5[71]

Table 29. Overview of variables and technical terms for the model in Chapter 5

Variable name/ Technical term	**Description**	**Explanation**
ACT_CONS_PAT	*Activity consumption matrix*	Contains information about the resource consumption as measured by the costing system for each cost driver.
BE_AB	*Difference between the share of significantly overcosted and the share of undercosted products*	Measures whether more products are materially undercosted or overcosted (i.e., more than 5% difference to a product's true costs).
bl_size	*Batch-level size*	The share of batch-level resources and costs, such as set-ups, maintenance, etc.
CC	*Correlation Cut-off variable*	The minimum similarity (correlation) in consumption between two resources to be allocated together in a cost pool.
CD-Heuristic	*Heuristic for cost-driver selection*	Defines the heuristic for cost driver selection for each cost pool. As described, a cost pool may contain several resources that are grouped together (e.g. cost pool "marketing" containing different marketing activities). The heuristic describes the general rule after which one of the activities is chosen to be the cost driver (allocation base) for all resources in that cost pool. Hence a firm may only measure the usage of that cost driver (Balakrishnan et al., 2011).
COR1	*Correlation between volume resources*	Defines the correlation between resource consumption on the unit-level (in the original model).
COR2	*Correlation between batch resources*	Defines the correlation between resource consumptions on the batch-level (in the original model).
CP	*Number of Cost Pools*	Number of cost pools a firm employs to allocate indirect costs to individual cost objects.

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[71] A similar table can also be found in the online appendix of Schmidt, M., Mertens, K. G., & Meyer, M. (2023). Cost hierarchies and the pattern of product cost cross-subsidization: extending a computational model of costing system design. *PLOS ONE, 18*(9). doi: 10.1371/journal.pone.0290370

Table 29 (continued).

CP-Heuristic	*Heuristic to allocate resources into cost pools*	Defines the heuristics chosen to group resources into cost pools. For instance, one approach may be to group similar resources into one cost pool (e.g., all marketing activities and costs into the “marketing pool”). The heuristics are described in the body of the paper or in the appendix of the ABL framework.
DENS	*Density of the resource consumption matrix (RES_CONS_PAT)*	Defines the degree of resource sharing between all products in the product portfolio. Higher degrees of resource sharing may reflect a mass-production process where product variants differ only marginally (Balakrishnan et al., 2011). Low degrees of resource sharing may reflect highly specialized single-unit production with high cost traceability (Kerremans et al., 1991).
DISP1	*Number of "big” resources*	Defines the number of “big” resources. “Big” resources reflect high costs that carry a large fraction of total costs. For instance, this may be the total salary costs in labor-intensive production.
DISP2	*Share of costs that are assigned to the “big” resources*	Defines the share of total costs that fall onto the “big” resources and hence defines the centralization of the firm’s production processes on a few resources.
fl_size	*Facility-sustaining-level size*	The share of resources and costs that are facility-sustaining-level, such as CEO pay or facility rent.
MISCPOOLSIZE	*Relative share of costs in MISCPOOL*	Share of total costs that are allocated to the miscellaneous cost pool. The miscellaneous cost pool reflects a cost pool that is not directly associated with a specific group of activities or resources and contains resources that cannot be allocated to other cost pools and are thus grouped together.
MXQ	*Production quantities per product*	Defines the production quantities (i.e., realized demand) of single products in the observed period.
Non_unit_size	*Non-unit-level size*	Share of resources that is *not* on the unit-level. In other words, resources that are not consumed in the production of single units.
NUMB_PRO	*Number of products*	Number of individual products in the product portfolio.
NUMB_RES	*Number of resources*	Number of individual resources (costs) consumed by the firm.

Table 29 (continued).

PCB	*Benchmark costs of a cost object*	The true costs of individual products, based on the actual resource consumption of an individual product. Firms can only calculate product costs based on the simplified costing system (PCH) and therefore possess no information about these true costs (PCB).
PCH	*Heuristics costs of a cost object*	Reflects the product costs reported by the costing system and is therefore based on simplified calculation. These costs deviate from the true costs (PCB) because a costing system only captures an aggregated and simplified picture of the true resource consumption [4].
Percentage Error (PE)	*PE = (PCH – PCB)/PCB*	Reflects the percentage deviation between true costs and reported costs of a product. Again, because true costs (PCB) are not attainable in empirical settings, the percentage error PE can only be calculated in artificial settings, such as a simulation experiment.
pl_size	*Product-sustaining-level size*	The share of resources and costs that are product-sustaining-level, such as product design activities, manufacturing planning, etc.
Q_VAR	*Disparity in production quantities*	Defines the disparity between production volumes of different products. Individual product variants may be produced in different quantities, with some products being so-called “high-runner” products and others being exotic, highly customized products (Elmaraghy et al., 2013). The former may likely be produced in larger quantities than the latter. Q_VAR defines the disparity between such different product variants.
RCC	*Resource costs*	The resource cost vector contains the overall costs for all individual resources of the firm. This information may be available from financial accounting (Balakrishnan et al., 2012a) in a firm’s financial statements.
RES_CONS_PAT	*Resource consumption pattern matrix*	The resource consumption matrix contains full and true information about the resource consumption of every single resource by every product. The resource consumption may reflect the actual and full activities and production process, or bill of materials (Anand et al., 2023) that arise to produce each product once, based on the production quantities MXQ.
TC	*Total Costs*	The total costs of a firm that arise when producing the quantities given in MXQ. Can

		also be seen as the total costs from a firm’s financial statement.

Table 29 (continued).

ul_size	*Unit-level size*	The share of resources and costs that are unit-level, such as direct labor, machine hours, etc.
VB_PATTERN	*Variable for the product cost cross-subsidization pattern.*	The employed variable to measure the strength of the product cost cross-subsidization pattern. The larger the value for this variable, the greater the overcosting (undercosting) bias for high (low) volume products.
VolumeDriver	*Indicator variable or the employed type of cost driver*	Indicates which type of cost driver is employed in a costing system. The type of cost driver primarily defines whether a costing system is seen as an ABC system or as a volume-based costing system (Labro, 2006a).

9.6 APPENDIX 6: NUMERICAL EXAMPLE FOR PRODUCT-LEVEL ERROR INVESTIGATIONS

Practical Example: Industrial contract manufacturing

Order: 10 cases for switchgear, including 2 for special use under high security standards. The following resources will be utilized: engineer, sheet metal bending machine, automatic welding system.

Product 1 – Regular Case for Switchgear

The engineer checks the feasibility of the order and develops the program for the two machines. In the manufacturing process, sheet metal is first bent and then welded.

Product 2 – Special Case for Switchgear

Essentially the same product, but with increased safety requirements. Therefore, the welding process is more complex, and the welds need to be inspected.

True Consumption of Resource Capacity of the Welding Engineer (non-unit level)

The engineer's costs (the salary) amount to €2,500. Capacity is consumed by checking the order and developing the CAM programs for both machines, which requires 80% of capacity. Since this activity is relevant to both products and independent of the production volumes, the consumption is attributed equally to both products. The remaining capacity is needed for developing a concept for inspecting the welds and adapting the CAM program of the welding system for Product 2.

True Consumption of Resource Sheet Metal Bending Machine (unit level)

The costs incurred by the use of the bending machine amount to a total of €1,000. The costs are determined by machine hourly rates. The process is the same for both products and takes the same amount of time - so the costs are proportional to the production quantity.

True Consumption of Resource Automatic Welding System (unit level)

The costs incurred by the use of the welding equipment amount to a total of €3,000, which are also determined by machine hourly rates. Due to the special requirements of Product 2, the process takes twice as long as for Product 1, thus resulting in higher costs.

Production Environment

$NUMB\_PRO = 2$ Products $\quad NUMB\_RES = 3$ Resources

$DENS = 1$ (Degree of resource sharing) $\quad Demand = (8 \quad 2)$

Deriving the Resource Consumption Pattern (*RES_CONS_PAT*)

1. $RES\_CONS\_PAT = \begin{pmatrix} 0.4 & 1 & 1 \\ 0.6 & 1 & 2 \end{pmatrix}$ Capturing resource consumption on per-unit basis
2. $RES\_CONS\_PAT = \begin{pmatrix} 0.4 & \mathbf{8} & \mathbf{8} \\ 0.6 & \mathbf{2} & \mathbf{4} \end{pmatrix}$ Multiplication of **unit-level** consumption by demand
3. $RES\_CONS\_PAT = \begin{pmatrix} 0.4 & 0.8 & 0.67 \\ 0.6 & 0.2 & 0.33 \end{pmatrix}$ Relative consumption of total resources

Calculating the Benchmark Product Costs (*PCB*) with given Resource Costs (RCC)

$$PCB = RCP \cdot RCC = \begin{pmatrix} 0.4 & 0.8 & 0.67 \\ 0.6 & 0.2 & 0.33 \end{pmatrix} \cdot \begin{pmatrix} 2.500€ \\ 1.000€ \\ 3.000€ \end{pmatrix} = \begin{pmatrix} 3.800€ \\ 2.700€ \end{pmatrix}$$

$pcb = \begin{pmatrix} 475€ \\ 1.350€ \end{pmatrix}$ Per-unit Benchmark Product Costs

Costing System

$CP = 1$ Cost Pool

$heuristic\ for\ Cost\ Driver\ selection: BIGPOOL$

In practice, all resource costs are recorded in the cost center *Production* (aggregated in one *CP*). To determine reported product costs (*PCH*), the consumption of the resource *welding system* is selected as cost driver and mapped as an Activity Consumption Pattern (*ACT_CONS_PAT*).

$$PCH = ACP \cdot CP = \begin{pmatrix} 0.67 \\ 0.33 \end{pmatrix} \cdot (6.500€) = \begin{pmatrix} 4.333{,}33€ \\ 2.166{,}67€ \end{pmatrix}$$

$pch = \begin{pmatrix} 541{,}67€ \\ 1.083{,}33€ \end{pmatrix} \quad Percentage\ Error = \begin{pmatrix} 14\%\ overcosted \\ -20\%\ undercosted \end{pmatrix}$

Relating Product Characteristics to the Percentage Error (*PE*) – are there robust trends?

9.7 APPENDIX 7: COST DRIVER CLASSIFICATION IN THE CASE STUDY OF A GERMAN VALVE MANUFACTURER

Table 30. Cost Drivers employed in the costing system of the valve manufacturer

ID	Name	Resource tier
RES-001	Prod Machine 1	Unit-level
RES-002	Prod Machine 2	Unit-level
RES-003	Prod Machine 3	Unit-level
RES-004	Prod Machine 4	Unit-level
RES-005	Prod Machine 5	Unit-level
RES-006	Stock	Non-unit-level
RES-007	Prod Machine 6	Unit-level
RES-008	Operations	Non-unit-level
RES-009	Prod Machine 7	Unit-level
RES-010	Prod Machine 8	Unit-level
RES-011	Prod Machine 9	Unit-level
RES-012	Prod Machine 10	Unit-level
RES-013	Logistics 1	Non-unit-level
RES-014	Welding	Non-unit-level
RES-015	Prod Machine 11	Unit-level
RES-016	Logistics 2	Non-unit-level
RES-017	Prod Machine 12	Unit-level
RES-018	Prod Machine 13	Unit-level
RES-019	Prod Machine 14	Unit-level
RES-020	Sandblasting	Non-unit-level
RES-021	Prod Machine 15	Unit-level
RES-022	Prod Machine 16	Unit-level
RES-023	Prod Machine 17	Unit-level

Note. RES = Resource