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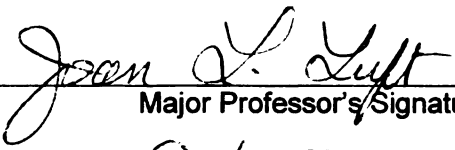
OVERHEAD COST POOL CLASSIFICATION AND
JUDGMENT PERFORMANCE

presented by

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of the requirements for the

DOCTORAL degree in ACCOUNTING


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OVERHEAD COST POOL CLASSIFICATION AND JUDGMENT PERFORMANCE

By

Matthew Christian Mastilak

A DISSERTATION

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ABSTRACT

OVERHEAD COST POOL CLASSIFICATION AND JUDGMENT PERFORMANCE

By

Matthew Christian Mastilak

This dissertation addresses the research question: does an organization's choice of overhead cost pool classification affect individuals' predictive judgments about overhead costs? I use psychology research to develop hypotheses about how overhead cost pool classification affects the expected accuracy of participants' predictions of a target overhead cost based on their estimation of the coefficients relating the target overhead cost to four predictor overhead costs. The predictor costs are located either within the same overhead pool as the target cost or in another pool. I vary relationships among the costs such that the larger predictor-target coefficient is either within a single cost pool or across different cost pools, and the relationships are positive or negative. I hypothesize that implicit coefficients on predictors within the same pool as the target cost will be estimated more accurately than implicit coefficients on predictors in a different pool. I also hypothesize that predictions of the target cost are affected by an interaction of the location of the stronger predictor and the sign of the relationships. As hypothesized, participants estimate implicit coefficients within a pool more accurately than coefficients across pools. Further, the location of the stronger predictor and the sign of the relations interact, such that the effect of the location of the stronger predictor on judgment accuracy is greater when relationships among costs are negative than when they are positive. I thus provide theory-consistent evidence of a cognitive effect of overhead cost pool classification in addition to informational effects modeled by the analytic literature.

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DEDICATION

This dissertation is dedicated to my wife Tina, who supported me emotionally and financially throughout my graduate work, and without whom I would never have been able to finish this work, my daughter Elizabeth, who has made my life immeasurably more joyous, and any and all children with whom God blesses us in the future. It is for my family that I chose this path.

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TABLE OF CONTENTS

LIST OF TABLES	viii
LIST OF FIGURES	ix
I. Introduction	1
II. Literature review and Hypothesis Development.....	5
Overhead cost pool classification	5
Example of a prediction task.....	7
Variation in overhead cost pool classification	8
Overhead cost pool classification and beliefs about costs	15
Beliefs about costs, attention allocation and judgment performance.....	17
Effect of cost behavior on judgment performance.....	19
Hypothesis development.....	22
Hypotheses 1 and 2: Coefficient estimation errors	24
Hypothesis 3: Prediction accuracy of overhead costs.....	27
III. Research design	32
Experimental design.....	32
Participants.....	34
Procedure and task	34
Measurement of variables.....	37
IV. Results	40
Hypotheses 1 and 2	42
Hypothesis 3.....	45
V. Discussion and conclusion.....	59
Appendix.....	65

References.....	106
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LIST OF TABLES

Table 1: Experimental design	33
Table 2: Experimental parameters	37
Table 3: Manipulation checks	41
Table 4: Hypotheses 1 and 2	43
Table 5: Sensitivity analysis: across-pool minus within-pool implicit coefficient errors by cost behavior condition: Each cost behavior condition contrasted with the mean of the other three cost behavior conditions	46
Table 6: Hypothesis 3	47
Table 7: Supplementary analysis	52

LIST OF FIGURES

Figure 1: Two-stage overhead cost allocation	6
Figure 2: Overhead cost pool classifications	13
Figure 3: Conceptual depiction of lens model method	21
Figure 4: Overhead cost pool classification and cost behavior.....	23
Figure 5: Graphical presentation of Hypothesis 3	30

I. INTRODUCTION

A fundamental function of accounting is the combination of individual accounts into groups of accounts. For example, external financial reporting and tax return preparation involve the reporting of hundreds or thousands of individual accounts in several dozen lines on financial statements or tax returns. Similarly, organizations classify individual overhead cost accounts into overhead cost pools. In this dissertation I examine how different overhead cost pool classification decisions affect judgment performance of individuals who use accounting reports. Throughout this dissertation, I use the label “overhead cost pool classification” to describe the assignment of individual overhead cost accounts to specific overhead cost pools.

Pooled overhead costs are the numerator of the ratio used to allocate overhead costs to cost objects such as products, services or customers. Prior literature on overhead cost pools has focused mainly on the *denominator* of the cost allocation rate calculation (the allocation base or cost driver), with little consideration of questions about the *numerator* alone. The literature has focused mainly on how cost driver choices and the degree of aggregation of costs into cost pools affect errors in cost allocations and whether non-volume cost drivers exist (Noreen 1991; Datar and Gupta 1994; Anderson 1995; Christensen and Demski 1995, 1997; Ittner et al. 1997). The literature has not fully investigated either the causes or the effects of organizations’ decisions about cost pool classification; thus, there is a lack of evidence on how classifications might affect individuals’ judgment. Individuals within organizations often require information to support decisions about individual cost accounts within cost pools, and thus research on effects of overhead cost pool classification on such decisions is valuable. I partially

address this gap in the literature by asking the research question: how does an organization's choice of overhead cost pool classification affect individuals' predictive judgments about overhead costs?

In this dissertation I examine a setting in which individuals receive reports about both overhead cost pool totals and individual overhead cost accounts within the pools. That is, the individual overhead costs are reported within their overhead cost pools. Individuals use these reports in a budgeting task that requires the prediction of the variable portion of an overhead cost (the "target cost"). Consistent with empirical evidence on managerial decisions (e.g., Datar et al. 1993), I focus on judgments about relationships among individual overhead costs within and across overhead pools, rather than judgments about relationships between overhead costs and cost allocation bases (i.e., cost drivers). I use psychology research to develop hypotheses about how overhead cost pool classification affects the accuracy of participants' predictions of a target overhead cost based on other overhead costs that may be predictive of the target (the "predictors").

I use an experimental research design in which participants make predictions about the target based on information about the predictors. The predictor costs are located either within the same overhead pool as the target cost or in another pool. Participants' predictions of the target cost are based on their estimate of the implicit coefficients relating the target to the various predictors.¹ I vary the relationships among costs in two ways. First, the location of the stronger predictor-target relationship is varied such that it is either within a single cost pool or across different cost pools. Second, the relationships

¹ I model participants' judgments using regression and generate estimates of the intercept and implicit coefficients in their prediction models. Participants do not directly estimate the coefficients relating the target cost to the predictors.

among costs are either positive or negative. These manipulations allow me to examine the effects on judgment of different overhead cost pool classification decisions in settings with differing cost behaviors (e.g., costs that are substitutes vs. complements).²

Based on psychology research, I predict that overhead cost pool classification affects judgment performance by directing individuals' attention toward within-pool relationships and away from across-pool relationships. Thus, I hypothesize that individuals will estimate within-pool implicit coefficients more accurately than across-pool implicit coefficients. I further expect that, consistent with evidence from the psychology literature, relationships to which less attention is allocated are underestimated rather than randomly misestimated (e.g., Broniarczyk and Alba 1994). Thus, individuals will tend to underestimate across-pool predictors more than within-pool predictors. I also predict that accuracy of individuals' predictions of the target overhead cost is an interactive function of the sign of the relationships among costs and the location of the stronger predictor, such that the effect of the location of the stronger predictor on judgment accuracy is greater when relationships among costs are negative than when they are positive.

The experimental results are generally consistent with hypotheses. Participants' predictions and their implicit coefficients exhibit patterns consistent with overhead cost pool classification affecting their judgments about costs. First, participants' estimates of the implicit coefficients relating predictor and target overhead costs are more accurate when predictor and target are within the same pool than when they are across pools.

² In this dissertation, I use the term "cost behavior" to describe whether the variable portion of target and predictor overhead costs are positively or negatively correlated with each other and whether the relation between target and predictor is weak or strong.

Second, participants underweight across-pool predictors more than within-pool predictors. Further, the sign and strength of the relationships among predictors and the target interact to affect the accuracy of participants' predictions of the target. The effect of overhead cost pool classification on judgment accuracy is greater when relationships among costs are negative than when they are positive. Finally, supplemental analysis provides evidence that overhead cost pool classification affects the allocation of attention across different predictors, and the allocation of attention affects prediction accuracy. I thus provide theory-consistent evidence of a cognitive effect of overhead cost pool classification in addition to informational effects modeled by the analytic literature.

This study considers subjective judgments about overhead costs. Subjective judgment is used often in organizations (MacKinnon and Bruns 1992; Kaplan and Norton 1996; Ittner et al. 2003), and thus it is an important topic for research. Even a formal statistical analysis such as a multiple regression analysis will only increase judgment accuracy if the appropriate relationships are examined (i.e., if appropriate variables are included in the regression). When performing formal statistical analyses, individuals often use subjective judgment to choose relationships to examine and the functional form of those relationships. My results imply that overhead cost pool classification can affect *which* relationships are examined as well as *how accurately* they are estimated. Thus, overhead cost pool classification may influence formal statistical analyses of overhead costs as well as subjective judgments.

The rest of this dissertation is organized as follows. Chapter 2 presents the literature review and hypothesis development. Chapter 3 describes the research design. Chapter 4 presents results, and Chapter 5 concludes.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

First, I will introduce accounting literature on overhead cost pool classification. Then, I will provide an example of a judgment task that is affected by organizations' overhead cost pool classification decisions. Next, I explain why these overhead cost pool classification decisions vary across organizations. Then, I use findings from psychology literature to describe (1) how variation in overhead cost pool classification will affect individuals' beliefs about costs, (2) how those beliefs will affect individuals' allocation of their attention when they perform the task, and (3) how attention allocation affects judgment performance in the task. Further, I make predictions about how different cost behaviors will affect judgment performance in the task. Finally, I state my hypotheses.

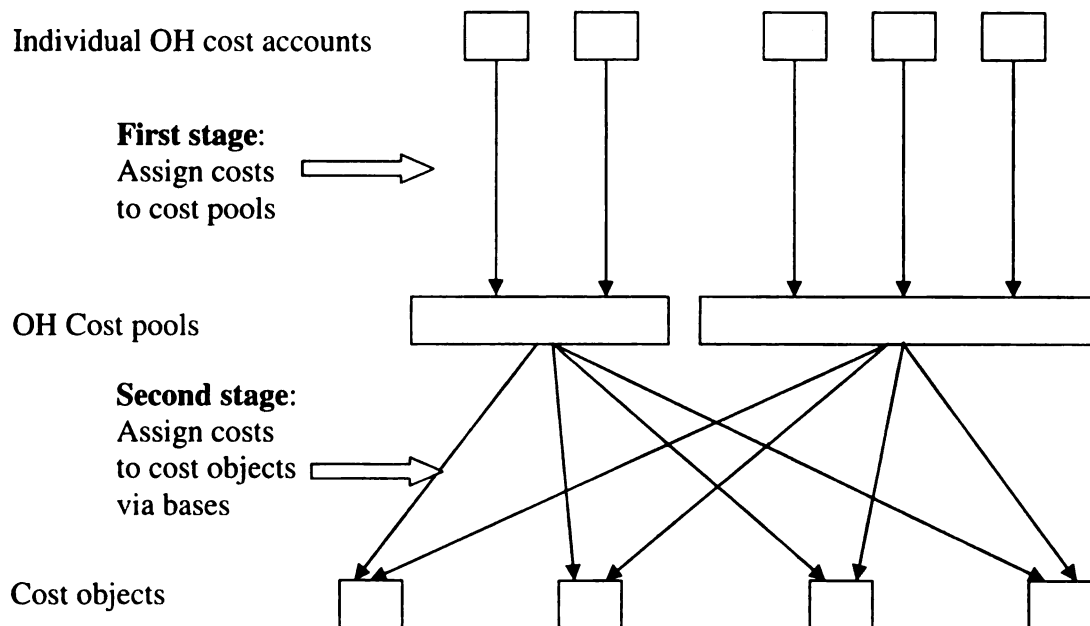
Overhead cost pool classification

Organizations' decisions regarding the allocation of overhead costs to cost objects can be modeled as a two-stage process, as shown in Figure 1 (Cooper and Kaplan 1999).

Prior academic literature on overhead cost pool classification has focused primarily on the second stage. Analytical literature has considered the effect of interactions between organizations' cost functions and overhead cost pool classification on the cost allocation error reported by various cost allocation systems (e.g., Noreen 1991; Datar and Gupta 1994; Christensen and Demski 1995, 1997; Bromwich and Hong 1999). Empirical literature has typically examined the validity of claims that important cost drivers other than production volume exist (e.g., Foster and Gupta 1990; Banker et al. 1995; Anderson 1995; Ittner et al. 1997). Experimental literature has examined the effects of cost system accuracy, economic complexity and different types of feedback on cost forecasting and product pricing/output decisions (Gupta and King 1997; Briers et al.

1999), and the interaction of cost system and incentives on innovation, efficiency and profitability in teams (Drake et al. 1999). To my knowledge, there is no literature on the effects of overhead cost pool classification on individuals' judgment performance about individual overhead costs.

Figure 1: Two-stage overhead cost allocation



This figure depicts the two-stage process for assigning overhead cost accounts from the chart of accounts to cost objects. In the first stage, overhead costs are assigned to overhead cost pools. In the second stage, overhead costs from the overhead cost pools are assigned to cost objects via allocation bases.

The potential for an effect of overhead cost pool classification on individuals' judgment performance is an important topic for research. There is evidence that overhead costs can be related to costs in other overhead cost pools in statistically and economically significant ways. For example, Anderson (1995) documents strong negative correlations

among setup costs, accounted for in a setup cost pool, and power costs, accounted for in an administrative cost pool. Ittner et al. (1997) document significant correlations among costs in different pools and at different levels of the activity-based costing hierarchy.

There is also evidence that relationships among costs in different cost pools are difficult for individuals to estimate. Joshi et al. (2001) report that managers grossly underestimate the magnitude of environmental regulation compliance costs that are “hidden” in non-regulatory cost pools.

Example of a prediction task

Consider the following example of a task an individual in an organization might face. As part of an organization’s operating budgeting process, the individual must predict the next month’s expected spoilage costs for each of several similar manufacturing plants. Unlike such costs as direct labor, spoilage costs are not the direct result of a spending decision, but rather an indirect result of a variety of other spending and operating decisions. The individual’s task is to predict spoilage cost from levels of spending on other overhead costs based on relationships among overhead costs observed in, and learned from, a prior month’s report. Specifically, the individual uses spending on inspection and supervision as predictors of spoilage costs. Assuming a linear, additive relationship between spoilage, inspection and supervision, the model is $Spoilage = Constant + \beta_1 Inspection + \beta_2 Supervision + error$. To successfully predict spoilage, the individual must estimate the constant (i.e., the fixed cost component of spoilage cost) and β_1 and β_2 , the coefficients on inspection and supervision (i.e., the components of spoilage cost that vary with inspection and supervision). The sign and magnitudes of the

coefficients will depend on the organization's cost function.³ That is, β_1 and β_2 may be positive or negative (or zero), and β_1 may be larger or smaller than β_2 . Further, the organization's overhead cost pool classification will affect whether inspection and/or supervision costs are in the same pool as spoilage costs. The next section discusses reasons why there can be variation in organizations' overhead cost pool classifications.

Variation in overhead cost pool classification

Relationships among overhead costs within and across cost pools will vary across organizations because organizations have different purposes for classifying overhead costs into pools. Two possible purposes are considered here: product costing and responsibility accounting.⁴

Product costing

One important purpose for classifying overhead costs into pools is the allocation of costs to products or services for such purposes as pricing, deciding whether to drop a product from the product line, determining optimal input mixes, and designing products to minimize cost (hereafter "product costing"). If product costing is the primary purpose of an organization's cost accounting system, then the organization will likely choose to assign to the same cost pools those overhead costs that are strongly positively correlated with each other (Garrison et al. 2006; Horngren et al. 2002; Kaplan and Cooper 1996). Overhead cost pool classification decisions that result in pools containing costs with

³ The magnitude of the constant (the fixed portion of the overhead cost) will also depend on the cost function. However, in this dissertation I focus only on coefficients (the variable portion of the overhead cost).

⁴ Other reasons exist, such as inventory valuation for external reporting purposes, that may also affect overhead cost pool classification decisions (Kaplan and Cooper 1999).

stronger positive within-pool correlations will minimize product costing errors (Noreen 1991; Christensen and Demski 1995; Bromwich and Hong 1999).

Noreen (1991, 163), discussing the requirements for a costing system to provide costs that are appropriate for product-drop and product-design decisions, writes,

[A] well-specified ABC system exists in which product costs are avoidable costs and activity costs are incremental costs if and only if: 1) the underlying cost function...can be partitioned into cost pools, each of which depends only upon a single activity; 2) the cost in each pool is strictly proportional to its activity, and 3) each activity can be divided among products in such a way that the portion attributed to each product depends only upon that product.”

If costs within a pool are all proportional to a single activity, then it follows that the costs will be highly correlated with each other. Bromwich and Hong (1999) extend Noreen’s (1991) analysis; consistent with Noreen (1991) they report that for a pooled accounting system to provide incremental costs for pricing, product portfolio and make-or-buy decisions, the technology must be locally homothetic and the overhead cost pool classification decisions must reflect that homotheticity:

A necessary condition for the construction of a cost pool is therefore that there must exist a specific aggregate input (in the accounting context, an aggregate cost driver) reflecting a constant mix of elementary inputs for the cost pool irrespective of volume which implies local homotheticity of cost pool technology. Thus, local homotheticity allows a single cost driver to be used for a cost pool irrespective of volume. (50)

Again, the existence of a cost driver as a “specific aggregate input” and a “constant mix of elementary inputs” mean that for a cost driver to summarize the costs within a pool, the costs within that pool must be correlated with that activity and with each other.

Similarly, Christensen and Demski (1995) model a firm’s cost-minimizing input-mix decision and consider the effect of cost pools on errors in costs reported by a cost system. They report,

In particular, we are accustomed to grouping factors in cost pools. Classically, this makes sense of the factor quantities respond in like fashion to the underlying technology and economic forces. Intuitively, this means we use the factors *in a pool in roughly the same manner*. Interactions with other factors are common across factors *in the pool*. (p. 16; emphasis added)

Thus, in comparing the “classical” model of cost to the “modern” or ABC model, Christensen and Demski (1995) state that in order for the “modern” model to report costs within pools without error, the use of inputs (and the resulting costs of those inputs) within a pool must be proportional to each other (that is, highly correlated). In addition to the proper specification of inputs and costs within pools, Christensen and Demski (1995) also identify a requirement of the relationships between different pools. “Cross pool elasticities must be zero, however, if the factor usage in a particular pool is to be independent of prices for factors outside the pool” (17). In the classical model, input prices determine input quantities for a specified technology and output mix. Thus, the requirement of zero cross-pool elasticities means the effect of a change in prices of factors in one pool must not affect the use of factors in other pools. In effect, then, costs in one pool must be uncorrelated with costs in other pools for a pooled cost accounting system to report costs appropriate for the input-mix decision.

In summary, if product costing is the primary determinant of overhead cost pool classification decisions, it is likely that costs within pools will be strongly correlated, and costs within a pool will be weakly correlated or uncorrelated with those in other pools.

Responsibility accounting

Another important purpose for classifying overhead costs into pools is responsibility accounting (that is, a system under which costs for which an individual or responsibility center is responsible are pooled to provide a summary statistic for that individual’s or responsibility center’s performance). If responsibility accounting is a

primary purpose for the cost system, within-pool relationships can be strong or weak.

Responsibility accounting purposes for cost system design may result in weakly correlated overhead costs being classified into a single pool. This may occur when a single individual or responsibility center has responsibility for weakly correlated costs, and when measurement error creates difficulty in dividing those costs into different pools (e.g., Datar and Gupta 1994).

For example, an employee may spend time on three different activities, and it is difficult to measure the time spent on each of two of those activities. The portions of that employee's compensation related to time spent on those two activities might then be recorded within a single pool even if they are weakly correlated, to prevent negative consequences that might result from allocating the time more finely but with error. Note also that in this example, there will likely be negative correlations among hours the employee spends on various activities. (Given a fixed amount of time spent in total, more hours spent on one activity results in fewer hours for other activities.) However, responsibility accounting does not *necessarily* create negative correlations among costs recorded within a pool.

On the other hand, overhead costs in one pool may be strongly correlated with overhead costs in a different pool, because different individuals or responsibility centers are responsible for the two costs, and accounting for them in separate pools facilitates calculations such as variances and responsibility center-level reports (Garrison et al. 2006; Horngren et al. 2002; Cooper and Kaplan 1999). Thus, in an organization whose overhead cost pool classification decisions are based primarily on responsibility accounting, it is possible (but not necessary) that weakly correlated overhead costs will

be classified into a single overhead cost pool and strongly correlated costs may be classified into different overhead cost pools.

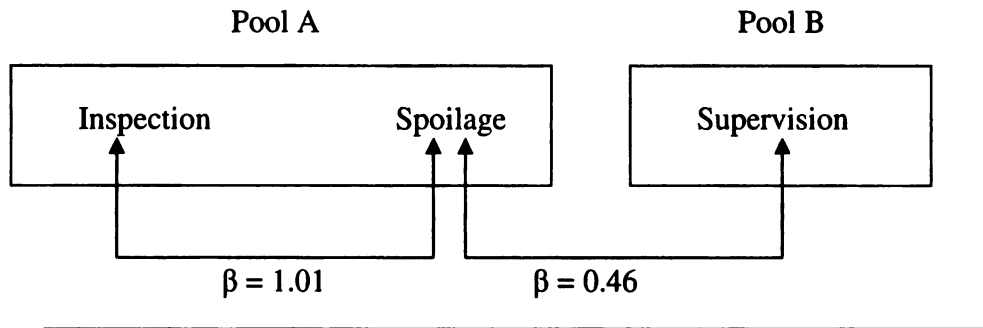
Example

The example of the prediction of spoilage costs from inspection and supervision costs can be used to illustrate overhead cost pool classification by product costing vs. responsibility accounting purposes. There are several overhead cost pool classification decisions the organization could make. Assume that inspection and supervision costs are uncorrelated and are in separate responsibility centers, so the organization has decided to account for these costs in separate pools. Further, assume the organization has decided to assign the three costs to two pools, and so must now decide whether to assign spoilage to the same pool as inspection or the same pool as supervision. Also assume that spoilage and inspection have a stronger relationship ($\beta_1 = 1.01$) and spoilage and supervision have a weaker relationship ($\beta_2 = 0.46$).⁵ Finally, assume that responsibility for and some influence over both spending on supervisors and reducing spoilage exist within a common responsibility center. Figure 2 presents the example graphically.

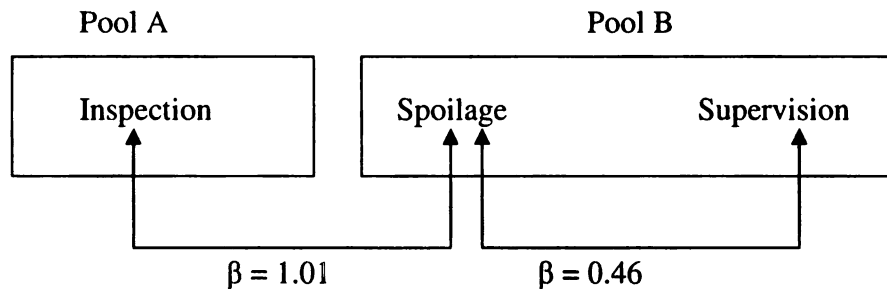
⁵ For simplicity, differences between larger and smaller coefficients are assumed to be statistically significant. Further, costs are assumed to have similar scales, so larger coefficients imply stronger correlations and more predictive validity.

Figure 2: Overhead cost pool classifications

Panel A: Cost pools based on cost allocation



Panel B: Cost pools based on responsibility accounting



This figure depicts two potential overhead cost pool classification decisions. In Panel A, costs are classified such that the stronger relationships (inspection and spoilage) is within a pool, and the weaker relationship (supervision and spoilage) is across pools. This classification might result if the organization decided that allocation of costs to cost objects is the most important use of the cost system.

In Panel B, costs are classified such that the stronger relationship (inspection and spoilage) is across cost pools, and the weaker relationship (supervision and spoilage) is within a pool. This classification might result if the organization decided that responsibility accounting use of the cost system is most important, and spoilage and supervision are the responsibility of the same manager.

Given the assumptions and the discussion above, there are two possible overhead cost pool classification decisions the organization can make. If allocating spoilage, inspection and supervision costs to cost objects is of primary importance, then the organization would likely include spoilage in the same cost pool as inspection. Figure 2, Panel A depicts this overhead cost pool classification. Spoilage has a stronger relationship with inspection than does supervision; as noted above, assigning spoilage and inspection to the same pool will allow for a better choice of allocation base than will assigning spoilage and supervision to the same pool. Note that in this overhead cost pool classification, there is a *stronger* relationship *within* a cost pool (spoilage and inspection) and a *weaker* relationship *across* cost pools (spoilage and supervision).

Alternatively, if responsibility accounting is of primary importance, then the organization would likely assign spoilage and supervision to the same cost pool, to allow the cost system to support clear responsibility accounting. Figure 2, Panel B depicts this overhead cost pool classification. Note that in this overhead cost pool classification, there is a *weaker* relationship *within* a cost pool (spoilage and supervision) and a *stronger* relationship *across* cost pools (spoilage and inspection).

In summary, there is likely variation in the overhead cost pool classification decisions made by organizations, based on different purposes for the overhead cost pool classifications. Whether and how these overhead cost pool classification decisions matter depend on how overhead cost pool classification decisions affect individuals' judgment performance. The following subsection reviews the accounting and psychology literatures and develops hypotheses about how overhead cost pool classification decisions are expected to affect judgment performance.

Overhead cost pool classification and beliefs about costs

The classification of costs into cost pools results in individual cost accounts being grouped together and given a common label (such as “quality control costs”). The grouping of individual items under a label has been investigated by the psychology literature on categorization (e.g., Markman and Gentner 2001). Categorization has been found to be a fundamental part of human information processing (Murphy and Medin 1985). The categories in which individual items reside, and the labels on those categories, have been found to influence the inferences individuals make about those individual items. Specifically, individuals infer that items given a category label are similar to other items given the same category label (Yamauchi and Markman 2000; Markman and Gentner 2001). Thus, when individuals make inferences about relationships among costs classified together in cost pools, they are likely to infer that the costs are similar to each other. Conversely, items categorized into different categories are assumed to be dissimilar (Yamauchi and Markman 2000; Markman and Gentner 2001). Thus, when individuals make inferences about relationships among costs classified into different pools, they will likely assume that costs classified into different cost pools are dissimilar.

Discussions of cost pool classification in accounting textbooks and literature typically focus on the correlations among costs within pools. Correlation among costs is the feature on which overhead cost pool classification is based (e.g., Christensen and Demski 1995; Kaplan and Cooper 1998; Horngren et al. 2002).⁶ Horngren et al. (2002, p. 142) write:

⁶ These examples refer to activity-based costing systems, and much of the discussion regarding overhead cost pool classification has been in the context of ABC systems. However, the choice of activities as the driver or allocation base is not required for the principle of overhead cost pool classification based on correlation to hold.

Each of the activity-related cost pools [is] homogeneous. Why? Because each activity cost pool includes only a narrow and focused set of costs (for example, setup or distribution). Over time, the costs in each activity-cost pool have a cause-and-effect relationship with the cost-allocation base for that activity (for example, setup-hours in the case of setup costs and cubic feet of packages moved in the case of distribution costs).

Similarly, Kaplan and Cooper (1998, p. 86) cite an internal training manual saying, “A resource comprises a *distinct and homogeneous* grouping of existing costs fulfilling a similar function...” (emphasis added). Also, Roth and Borthick (1991, p. 39) write that the assumption of homogeneity in activity-based costing models “means that the costs in each pool are driven by a single activity or by highly correlated activities. *Highly correlated* means that changes in the level of one activity are accompanied by proportional changes in the other activities” (emphasis in original).

These passages strongly imply that because costs within each pool move with a single activity driver, they move together with each other. Further, because each pool’s costs are “narrow and focused” or, alternatively, “distinct and homogeneous,” costs that are not highly correlated are classified into separate pools. Thus, correlation among costs is an important feature of individual costs that individuals will likely infer is similar among costs classified within a cost pool, and dissimilar among costs classified into different cost pools. Thus, in the absence of strong evidence to the contrary, students and practitioners of accounting are likely to believe that overhead costs within a pool (across pools) are positively and relatively strongly correlated (not correlated).

Despite the assumption in the literature about strong relationships being classified within pools, organizations’ overhead cost pool classification decisions vary, as described above. Therefore, individuals within organizations will sometimes use accounting information in which strong correlations are across-pool rather than within-pool, for

example, when overhead cost pool classification is based on responsibility accounting. In these circumstances, individuals will have knowledge of some, but not all, of the relationships among costs. Individuals have limited cognitive resources (i.e., they are boundedly rational), and they will likely estimate accurately and retrieve from memory only the more important relationships or those they encounter more frequently (Anderson 1990). Individuals may not have learned about certain relationships because those relationships may have been relatively unimportant in the past, or because information about those relationships was not available. Moreover, relationships that were and remain important may change in magnitude over time. For those relationships for which individuals do not have current knowledge, individuals may rely on overhead cost pool classification as a source of beliefs about relationships among overhead costs.

The accuracy of individuals' estimates of relationships among overhead costs may be affected by organizations' overhead cost pool classification decisions and the relationships among overhead costs. Individuals' implicit estimations of relationships among overhead costs, and their resulting predictions of the target overhead cost, will be affected by both the allocation of attention among potential relationships and the cognitive difficulty of estimating those relationships that receive attention. The following analysis describes how overhead cost pool classification and cost behavior can affect attention allocation and estimation accuracy.

Beliefs about costs, attention allocation and judgment performance

Beliefs about relationships in data can affect the allocation of individuals' attention among the potential relationships (Brehmer 1974; Broniarczyk and Alba 1994; Luft and Shields 2001). Research in accounting and psychology has documented the

pervasive effects of individuals' beliefs on how they cognitively examine data and their resulting judgments in a variety of task settings, such as credit scoring, GPA and temperature prediction, consumer judgments of a price-quality relationship, and profit prediction (Muchinsky and Dudycha 1974, 1975; Sniezek 1986; Broniarczyk and Alba 1994; Luft and Shields 2001). Psychology research indicates that individuals examine potential relationships between a target and multiple predictors one predictor at a time, rather than simultaneously (Brehmer 1974). The order in which individuals examine relationships is influenced by their beliefs. Individuals examine potential relationships they believe to be more important earlier than relationships they believe to be less important (Brehmer 1974). Relationships examined earlier are estimated more accurately because individuals' limited cognitive capacity leads to fatigue, reduced cognitive effort and inconsistency in estimating relationships examined later (Brehmer 1974; Luft and Shields 2001). Thus, if individuals believe that overhead costs within (across) pools are likely (unlikely) to be related to each other, then overhead cost pool classification is expected to affect judgment accuracy. However, if individuals hold strong beliefs about relationships, but those relationships are not present in the data, those beliefs can overwhelm inspection of the data, individuals' judgments can be biased in the direction of their beliefs (Broniarczyk and Alba 1994).

Evidence from Joshi et al. (2001) is consistent with overhead cost pool classification affecting judgment performance among experienced managers. The authors found that large portions of the costs steel firms incur in complying with environmental regulations are accounted for in non-regulatory cost pools. These costs are misclassified because they are not easily identifiable as regulatory costs. For example, if a mill

switches from a cheaper, high-polluting coal to a more-expensive, cleaner-burning coal, the entire cost of the coal is counted as a raw material cost, even though the difference in coal prices is due to regulation and would not be incurred save for the regulation.

Managers at the firms studied are aware of the existence of across-pool relationships and the fact that some regulatory cost burden is “hidden.” Further, managers consider environmental regulation costs to be an important factor in their firms’ ability to compete. The managers thus have both the opportunity and the motivation to understand the magnitude of the relationships. However, the managers grossly underestimated the magnitude of regulatory costs – they estimated that about half the cost was hidden, while the authors estimate that up to 90% of the cost is hidden. In interviews, the managers said they believed their underestimation of the regulatory costs affected decisions such as performance evaluation and plant closure or continuance decisions. However, whether the overhead cost pool classification is the cause or the effect of managers’ beliefs about the magnitude of “hidden” regulatory costs is uncertain.⁷

Effect of cost behavior on judgment performance

The sign and strengths of relationships can affect the accuracy of individuals’ estimations of the relationships independently of attention-allocation effects (Brehmer 1974; Snizek 1986; Farrell et al. 2006). Even when individuals have correct beliefs about the sign of relationships, positive relationships are estimated more accurately than are negative relationships, indicating an inherent difference in the cognitive difficulty of estimating positive vs. negative relationships, all else equal. Thus, when individuals

⁷ That is, managers may have had beliefs that the amount of potentially hidden regulatory cost was small, and designed their regulatory cost pools based on those beliefs. The design of Joshi et al. (2001) does not support inferences about causality between overhead cost pool classification and managers’ beliefs.

attempt to revise beliefs about relationships among overhead costs, they are likely to do so more accurately when the costs are positively correlated than when they are negatively correlated. Further, psychology research indicates that relatively weak relationships (i.e., those with correlations below approximately 0.6) are generally difficult for individuals to estimate subjectively, while stronger relationships (i.e., those with correlations above approximately 0.6) are generally estimated more accurately (e.g., Broniarczyk and Alba 1994). Thus, the sign and strength of a relationship affect the accuracy with which it is estimated.

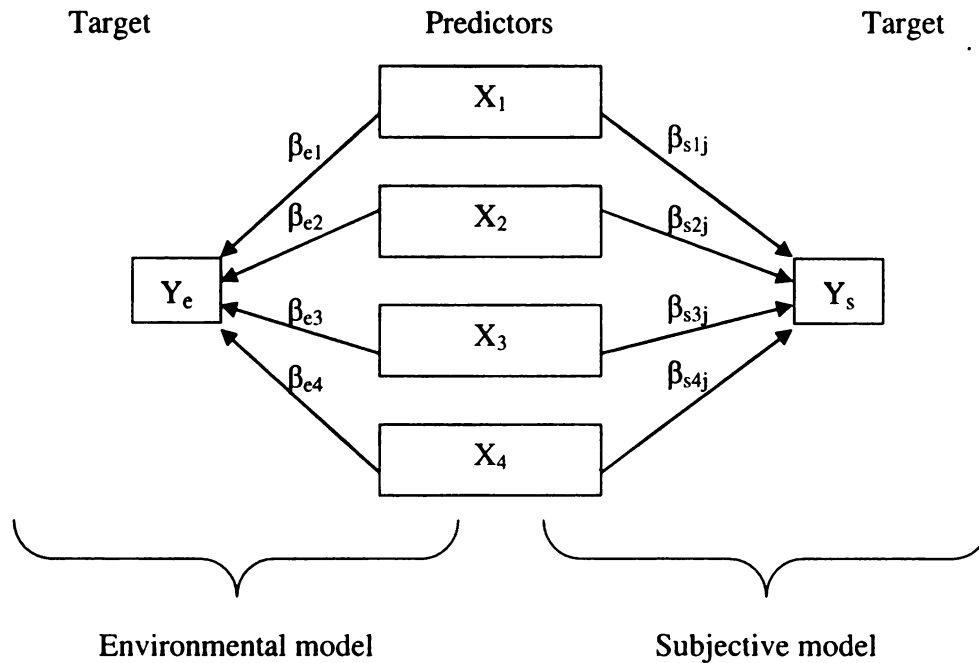
There is also evidence that beliefs about relationships and the sign of relationships interact to affect judgment performance. Snizek (1986, experiment 3) found that the effect of incorrect beliefs on judgment performance was greater when the relationships in the data were negative than when they were positive.

Consistent with psychology and accounting research, I use a lens model to analyze how and how well individuals learn and predict relationships from data.⁸ A conceptual depiction of the lens model is shown in Figure 3. The predictors in the center are the predictors individuals can use to predict the target. The environmental or true model is depicted on the left side of the figure; this model is derived from the data (Y_e and X_i) that are presented to individuals and that they could use to estimate the environmental coefficients (β_{ei} , where ei refers to the environmental coefficient on predictor i). The subjective model on the right side of the figure represents the model of individuals' subjective predictions of the target (Y_s) based on levels of the predictors.

⁸ For a thorough and recent treatment of the lens model in accounting research, see Luft and Shields (2001).

Lens model studies regress individuals' subjective predictions of the target on the predictors and estimate each participant's implicit coefficients (β_{sij} , where sij refers to participant j 's implicit coefficient on predictor i).

Figure 3: Conceptual depiction of lens model method



This figure presents a conceptual depiction of the lens model method. The predictors in the center are the four predictors individuals can use to predict the target. The environmental or true model is depicted on the left side of the figure; this model is derived from the data that is presented to individuals and that they could use to estimate the environmental coefficients (β_{ei} , where ei refers to the environmental coefficient on predictor i).

The subjective model on the right side of the figure represents the model of individuals' subjective predictions of the target based on levels of the predictors. Lens model studies regress individuals' predictions of the target on the predictors and estimate each participant's implicit coefficients (β_{sij} , where sij refers to participant j 's implicit coefficient on predictor i).

Hypothesis development

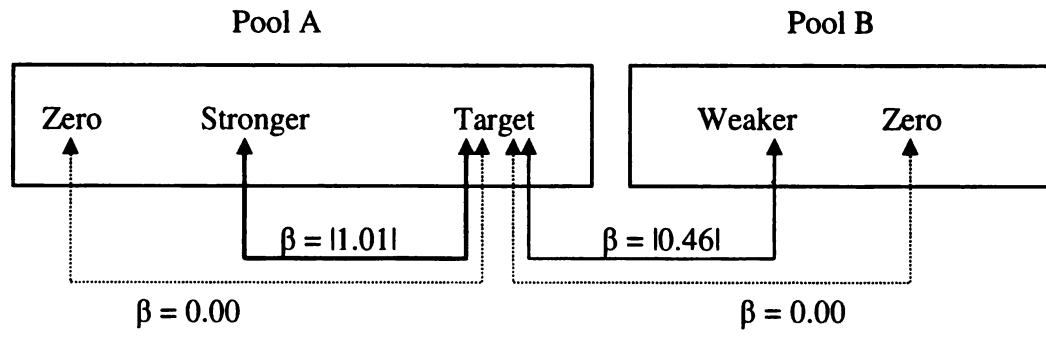
To aid the exposition of the hypotheses, I first briefly describe the experimental task. I examine an operating budgeting task in which participants predict the amount of the next month's expected spoilage costs in each of 20 similar manufacturing plants. The prediction is based on relationships among overhead costs that participants learn by examining the prior month's cost reports. The amount of reported spoilage costs is affected by two predictors (the "non-zero predictors").⁹ Two additional predictors are not actually predictive of spoilage (the "zero predictors"). The five overhead costs are assigned to two pools. Each pool contains one cost that is predictive of spoilage (a non-zero predictor) and one cost that is not predictive of spoilage (a zero predictor).

To examine whether the effect of overhead cost pool classification varies with variable cost behavior, I use two manipulations of cost behavior. First, I vary the pool location of the stronger predictor – the predictor with the larger coefficient is either within the same pool as spoilage or in the other pool (that is, across pools). Second, I vary the sign of the nonzero coefficients on the predictors – they are either positive or negative. Figure 4 depicts the overhead cost pool classification and cost behavior conceptually. Panel A presents the condition in which the stronger predictor relationship is within the same pool as spoilage; Panel B presents the condition in which the stronger predictor relationship is across pools.

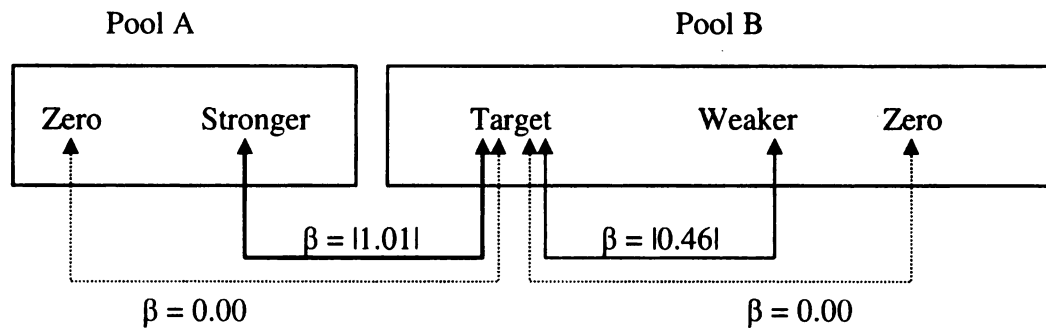
⁹ Throughout this dissertation, I use the label "predictors" to indicate the costs that participants could use to predict the target cost regardless of whether they are statistically significant predictors. The inclusion of zero-coefficient predictors in a setting in which participants are likely to expect positive correlations allows for an empirical test of this departure from participants' likely expectations, and allows for tests to determine the effect of overhead cost pool classification on participants' estimation of coefficients.

Figure 4: Overhead cost pool classification and cost behavior

Panel A: stronger relationship is within-pool



Panel B: stronger relationship is across-pool



This figure presents a conceptual depiction of the design of the experimental task. “Target” describes the target cost that the individual is to predict. “Stronger,” “weaker” and “zero” describe the relationships between the predictors and the target. The β coefficients on the arrows specify the strength of the relationships between the targets and the predictors. The boxes represent overhead cost pool classification boundaries. Note that in this example, all costs have similar scales, so larger coefficients imply stronger correlations and more predictive power. All differences between coefficients are statistically significant at $p < 0.05$.

Participants are told the expected signs but not the magnitudes of the relationships between spoilage and the predictors. To perform well on the task, participants must use the cost reports to estimate the relationships between spoilage and the other overhead

costs.¹⁰ They must then apply those estimates of the relationships to the next month's budget of the four overhead costs and predict spoilage based on budgeted levels of the four other costs. An example of the experimental materials is shown in Appendix A.

Hypotheses 1 and 2 make predictions about errors in participants' implicit coefficients on individual predictors. Hypothesis 3 predicts how variation in overhead cost pool classification and cost behavior affect the overall prediction accuracy of overhead costs.

Hypotheses 1 and 2: Coefficient estimation errors

As described earlier, individuals generally examine potential relationships sequentially, with relationships believed to be more important examined earlier and more accurately than those believed to be less important (Brehmer 1974; Luft and Shields 2001). Consistent with the accounting literature reviewed above, I expect stronger (weaker) within-pool and weaker (stronger) across-pool relationships to be consistent (inconsistent) with individuals' beliefs about the relationships among overhead costs assigned to cost pools when the individuals have no other strong sources of belief about the relationships among the costs. Because individuals likely believe that overhead costs classified within the same pool are strongly related and overhead costs classified across different pools are not strongly related, they will devote more attention to within-pool relationships and estimate them more accurately than across-pool relationships. I expect this effect even though in my research design, all participants examine statistically identical data sets, with detailed cost information available in all conditions, and my

¹⁰ Participants must also implicitly estimate the constant in addition to the coefficients on the predictors. However, large errors in estimating the constant are unlikely, as they would result in predicted levels of spoilage that are outside the range of those in the prior month's data.

research design includes relatively few potential predictors and offers a strong and direct financial incentive for optimal performance.

Beliefs can affect judgment accuracy in at least two ways. First, beliefs can affect the *bias* of individuals' judgments (Sniezek 1986; Billman et al. 1992; Broniarczyk and Alba 1994; Luft and Shields 2001). Because, in the absence of specific knowledge to the contrary, individuals likely believe that within-pool (across-pool) relationships exist or are more important (do not exist or are less important), they will exhibit a pattern of error biases consistent with these beliefs. For the non-zero predictors' coefficients, individuals will pay more attention to within-pool coefficients than to across-pool coefficients. Thus, individuals will estimate within-pool coefficients with relatively little bias. Because individuals will pay less attention to the across-pool coefficients, they tend to treat the across-pool coefficients as closer to zero than the data indicate. That is, individuals will underestimate across-pool non-zero predictors' coefficients more than within-pool non-zero predictors' coefficients.

For the zero predictors' coefficients, individuals will likely believe that the within-pool coefficients are non-zero. Broniarczyk and Alba (1994) present evidence that in the presence of strong beliefs about a relationship, individuals will make judgments as though such a relationship exists when in fact there is no relationship in the data. Thus, if individuals strongly believe that costs within pools are correlated, these beliefs may overwhelm the data, and the individuals may overestimate within-pool zero predictors' coefficients. However, individuals might not overestimate the within-pool coefficients for several reasons. First, individuals will pay significant attention to the within-pool relationships, and therefore individuals will estimate the within-pool relationships

accurately. Second, individuals have financial incentives to estimate coefficients accurately. And third, statistical relationships among the data in my setting are strong, which will improve the accuracy of individuals' coefficient estimates. Thus, I conclude that individuals are unlikely to overestimate within-pool zero coefficients.

The second way in which beliefs can affect judgment accuracy is by affecting the *variation* (that is, the random error) with which individuals estimate coefficients.

Estimates of relationships that are inconsistent with individuals' beliefs tend to have more random error than do estimates of relationships that are consistent with individuals' beliefs (Sniezek 1986; Luft and Shields 2001). Thus, because individuals without specific knowledge to the contrary will likely believe within-pool relationships are stronger or more likely to exist than across-pool relationships, within-pool coefficients will likely be estimated with less variation than across-pool coefficients. However, if individuals pay very little attention to across-pool coefficients, then the across-pool coefficients may be treated as though they are zero, and thus will exhibit little random error.

The above analysis leads to the following hypotheses in alternative form:

H1: Judgment accuracy will be higher (bias will be smaller and variation will not be larger) for within-pool non-zero predictors' coefficients than for across-pool non-zero predictors' coefficients.

H2: Judgment accuracy will be higher (bias will be smaller and variation will not be larger) for within-pool zero predictors' coefficients than for across-pool zero predictors' coefficients.

The existence of four types of coefficients (within- and across-pool; non-zero and zero correlations) means there are six possible pairwise comparisons. I have chosen to focus on the two pairwise comparisons for several reasons. First, Hypothesis 3 presents an omnibus test of prediction accuracy, including all coefficients. Second, there is not a well-developed theoretical prediction for the four coefficient pairs that I do not test.

Third, the pairs I test in hypotheses 1 and 2 allow for a clean test of whether differences in implicit coefficient estimation accuracy are due to differences in the overhead cost pool classification. That is, the untested pairs include a manipulation of both whether a coefficient is within-pool or across-pool *and* whether the environmental correlation is non-zero or zero. Thus, any test of those pairs is inherently a test of an interaction between overhead cost pool classification and cost behavior. Because of the lack of theoretical development and the fact that the emphasis in this portion of the paper is on overhead cost pool classification alone and not on its interaction with cost behavior, such a test would not be meaningful.

Hypothesis 3: Prediction accuracy of overhead costs

Hypotheses 1 and 2 make predictions about within-individual effects of overhead cost pool classification on implicit coefficient errors on *specific* predictors. Such evidence is important to understanding how overhead cost pool classification affects the accuracy of judgment in certain tasks (for example, estimating how much spoilage will change as a result of changing spending on one of the predictors). However, understanding how overhead cost pool classification affects performance on the overall cost prediction task requires understanding how cost behavior and *all* the individual coefficient estimates jointly affect cost prediction accuracy. Hypothesis 3 predicts how the interaction of overhead cost pool classification and between-individual manipulations of variable cost behavior affects a *set* of implicit coefficient errors and thus the overall accuracy of participants' predictions of overhead costs. In the following subsections I describe how I expect the location of the stronger predictor and the sign of relationships to affect individual implicit coefficient errors and thus the overall prediction of overhead costs.

Location of stronger predictor

Individuals likely have beliefs that costs within pools behave similarly, and costs across pools behave dissimilarly, in the absence of strong cues to the contrary. However, empirical evidence shows that costs in different pools can be statistically significantly correlated (Anderson 1995; Ittner et al. 1997; Joshi et al. 2001). When the stronger predictor is across pools, individuals will devote less attention to the stronger across-pool relationship because it is inconsistent with their beliefs, and thus will underweight it. Further, individuals will have difficulty estimating the within-pool relationship because of its relatively low magnitude (Broniarczyk and Alba 1994). Because all of the implicit coefficients will be estimated less accurately, I expect that *ceteris paribus*, accuracy of individuals' predictions of overhead costs will be higher when the stronger predictor is within-pool than when it is across-pool.

Sign of relationships

Overhead costs can be either positively or negatively correlated. As noted above, typical recommendations for cost system design assume that costs within pools are positively correlated. However, empirical evidence demonstrates that overhead costs can exhibit either positive or negative correlations (e.g., Datar et al. 1993; Anderson 1995; Joshi et al. 2001). Prior research in psychology and accounting finds that estimation of negative relationships is inherently more cognitively difficult, and thus less accurate, than estimation of positive relationships (e.g., Brehmer 1974). Thus, even if individuals are aware of the *existence* of a negative coefficient relating predictor costs to the target cost, they may be less able to estimate accurately its *magnitude* than they would if the coefficient were positive. Therefore, I expect that *ceteris paribus*, the accuracy of

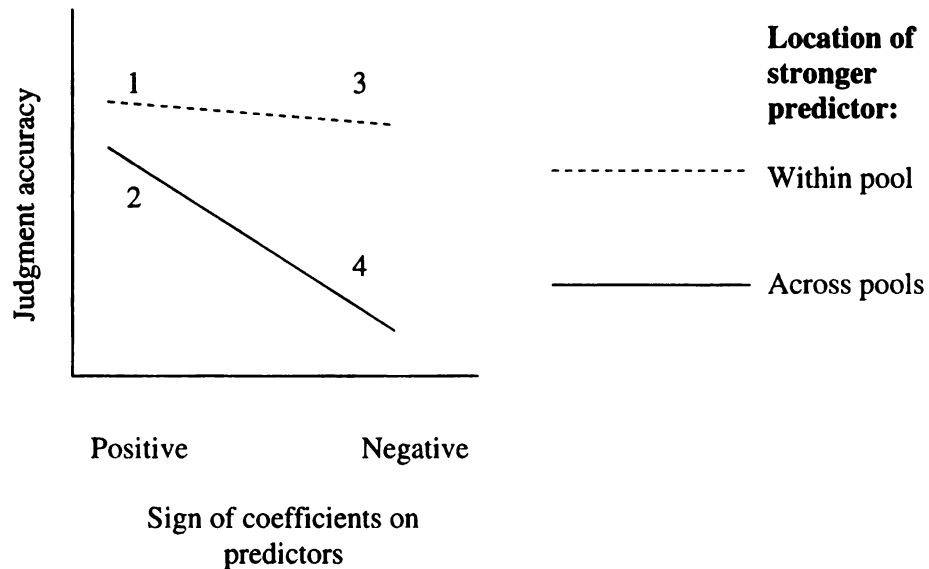
individuals' predictions of overhead costs will be higher when relationships between overhead costs are positive than when they are negative.

Note that in this study, all the non-zero predictors are either positively or negatively correlated with the target; that is, there are no cases in which signs are mixed. While empirical evidence indicates that both positive and negative correlations occur simultaneously in practice (e.g., Datar et al. 1993), I chose to include only single-sign cases in this study for simplicity.

Interaction of relative strength and sign

I expect that the location of the stronger predictor and sign of the relationships among costs will ordinally interact to affect judgment accuracy. The effect of the location of the stronger predictor will be larger when relationships among costs are negative than when the relationships are positive. The expected interaction is presented graphically in Figure 5.

Figure 5: Graphical presentation of Hypothesis 3



This figure presents the hypothesized interaction between the location of the stronger predictor (either within the same pool as the target cost or across pools) and the sign of the coefficients relating the predictors to the target (positive or negative).

When relationships among costs are *positive*, the reduction in prediction accuracy (1 – 2 in Figure 5) that results from the stronger predictor being across-pool rather than within-pool will be relatively small. Individuals will allocate less attention to the stronger predictor when it is in a different pool from the target cost compared to when it is in the same pool. However, because the relationships among costs are positive, estimation is not as cognitively difficult, and so individuals will be able to estimate the implicit coefficient on the stronger predictor with relatively high accuracy. Further, the cognitive difficulty of estimating the implicit coefficient on the weaker, within-pool predictor will be relatively small because of the positive sign and the relatively high attention it receives because it is within-pool. Thus, the effect on prediction accuracy of the stronger predictor being

across-pool rather than within-pool will be relatively small when relationships among costs are positive.

When relationships among costs are *negative*, the reduction in prediction accuracy (3 – 4 in Figure 5) that results from the stronger predictor being across-pool rather than within-pool will be relatively large. Individuals will allocate less attention to the stronger predictor when it is in a different overhead cost pool from the target cost compared to when it is in the same pool. The reduced attention individuals allocate to the stronger predictor will be insufficient to overcome the cognitive difficulty of estimating negative relationships, and individuals' estimates of the implicit coefficient on the stronger predictor will be less accurate. Further, the difficulty of estimating the implicit coefficient on the weaker, within-pool predictor will be exacerbated by the negative sign, despite the relatively high attention it receives because it is within-pool. Thus, neither implicit coefficient will be estimated accurately, and the effect on prediction accuracy of the stronger predictor being across-pool rather than within-pool will be larger when the relationships among costs are negative than when they are positive. That is, I predict the interaction will be of the form $3 - 4 > 1 - 2$. This prediction is consistent with evidence from Snizek (1986), who found that the effect on judgment accuracy of inconsistency between individuals' beliefs and actual data is larger when relationships are negative than when they are positive.

H3: Overhead cost prediction accuracy is an interactive function of the location of the stronger predictor and the sign of relationship between the predictors and the target.

III. RESEARCH DESIGN

Experimental design

The hypotheses are tested using an experiment with a 2 x 2 x 2 x 2 x 2 mixed design. There are two within-participant factors. The first within-participant factor is whether a predictor is within the same pool as spoilage or across pools (that is, in a different pool from spoilage). The second within-participant factor is whether a predictor has a non-zero coefficient or a zero coefficient relating the predictor to spoilage. There are three between-participant factors. The first between-participant factor is the location of the stronger predictor-target relationship, either within the same pool as spoilage or across pools. The second between-participant factor is the sign of the predictor-target relationships; they were all positive in one condition and all negative in the other. The third between-participants factor is the *label* of the costs. For half the participants, the predictors within the same pool as spoilage were labeled “inspection” and “testing,” while the predictors in the other pool were labeled “supervision” and “training.” For the other half of the participants, the labels were reversed, such that the predictors within the same pool as spoilage were labeled “supervision” and “training,” while the predictors in the other pool were labeled “inspection” and “testing.” This last factor was manipulated between participants to control for beliefs about relationships among costs with specific labels. There was not a main effect of label or a significant interaction between labels and other variables (all p values > 0.10); thus, this factor is omitted in all analyses reported below. The experimental design is shown in Table 1.¹¹

¹¹ Participants’ responses were collected in five sessions. A control variable for session did not result in a significant main effect or interaction with other variables; thus, session is omitted in all analyses.

Table 1: Experimental design**Quality control pool****Location of stronger relationship and sign****Within-pool**(1) *Positive*(2) *Negative***Across-pool**(3) *Positive*(4) *Negative***Quality control pool****Spoilage****Inspection****Testing**

--

1.01

0.0

--

-1.01

0.0

--

0.46

0.0

--

-0.46

0.0

Supervision pool**Supervisors****Training**

0.46

0.0

-0.46

0.0

1.01

0.0

-1.01

0.0

Supervision pool**Within-pool**(5) *Positive*(6) *Negative***Across-pool**(7) *Positive*(8) *Negative***Supervision pool****Spoilage****Supervisors****Training**

--

1.01

0.0

--

-1.01

0.0

--

0.46

0.0

--

-0.46

0.0

Quality control pool**Inspection****Testing**

0.46

0.0

-0.46

0.0

1.01

0.0

-1.01

0.0

The entries in the cells are the coefficients relating each predictor cost to spoilage. Each row, representing a between-participant cost behavior condition, can be read as the specific environmental model for that cost behavior condition, with the addition of a constant. The constant varied between positive and negative sign conditions (-\$24,145 and \$104,125, respectively). For example, for participants receiving the cost behavior described in row (1), $\text{Spoilage} = -\$24,145 + 1.01 \times \text{Inspection cost} + 0.46 \times \text{Supervisors cost}$. For participants receiving the cost behavior described in row (6), $\text{Spoilage} = \$104,125 - 1.01 \times \text{Supervisors cost} - 0.46 \times \text{Inspection cost}$.

The first between-participant factor was the location of the stronger predictor-target relationship (correlation = 0.91; coefficient = 1.01), either within the same pool as spoilage or across pools; the other relationship was the weaker one (correlation = 0.46; coefficient = 0.46). The second between-participant factor was the sign of the predictor-target relationships; they were all either positive or negative. The third between-participants factor was the label of the costs. For half the participants, the predictors within the same pool as spoilage were labeled "inspection" and "testing," while the predictors in the other pool were labeled "supervision" and "training." For the other half of the participants, the labels were reversed, such that the predictors within the same pool as spoilage were labeled "supervision" and "training," while the predictors in the other pool were labeled "inspection" and "testing." The first within-participant factor is whether a predictor is within the same pool as spoilage or across pools. The second within-participant factor is whether a predictor has a non-zero coefficient or a zero coefficient.

Participants

Eighty-one undergraduate business students enrolled in a cost-accounting class at a large public university volunteered to participate in the research. They were given course credit and \$5 for participating, and incentive-based pay from \$1 to \$10 based on their judgment accuracy. Three participants' responses were eliminated because their accuracy measures were influential outliers.¹² The final sample thus included 78 participants.

Procedure and task

Participants were given a paper-and-pencil task in which they were asked to assume the role of a controller in a manufacturing firm. As part of their firm's operating budgeting process, they were to predict spoilage costs for 20 similar manufacturing plants for the next month. Participants were asked to predict spoilage cost from the four other overhead costs (inspection, testing, supervisors, and training) in two overhead cost pools (quality control and supervision). Either inspection or supervisors (depending on the label condition) was strongly predictive of spoilage, and the other was weakly predictive. The other two costs (testing and training) were not predictive of spoilage. Each cost pool contained either the stronger or the weaker predictor and one of the zero-correlation predictors. The coefficient relating the stronger (weaker) predictor to spoilage was 11.011 (10.461). The relationship between spoilage and the two predictive costs is: $Spoilage = Constant \pm 1.01 \times Stronger \pm 0.46 \times Weaker + error$, where *Stronger* (*Weaker*) refers to

¹² Because mean squared error of predictions encompasses all potential causes of error, I use mean squared error to identify outliers. I regressed mean squared error on sign, location of the stronger predictor, and the interaction of sign and location to determine influential outliers using Cook's D. Two observations had values of Cook's D greater than $(4/n)$, a reasonable cutoff per Fox (1991), and were thus eliminated.

the cost with the stronger (weaker) relationship, and *Constant* = -\$24,145 and \$104,125 in the positive and negative conditions, respectively, and *error* is zero-mean noise. The rows in Table 1 describe the specific model for each condition individually.

Participants were told spoilage costs were not the direct result of a single spending decision but resulted from, and were predictable from, other spending decisions made during the month. Participants were given a learning data set that provided the prior month's cost data by plant, reported in the two cost pools (see Appendix).

To reduce noise, I attempted to set participants' beliefs about the sign of relationships with the following wording for the positive and negative conditions, respectively:

“Higher spending on one (or more) of these activities could lead to higher levels of spoilage costs being recorded, because more care is taken to identify and discard defective units before they are sent to customers,” or “[h]igher spending on one (or more) of these activities could lead to lower spoilage costs by improving production quality.”

Setting participant's beliefs about the sign of relationships reduces noise by reducing the likelihood that participants will attempt to estimate the relationship with an incorrect sign. Further, practicing managers may know the sign or direction of relationships among overhead costs without knowing the exact magnitude of those relationships.

Participants also received a judgment data set, in which next month's budgeted levels of the predictor costs were given, with blanks to fill in predictions of expected spoilage costs (see Appendix). Participants were allowed to use calculators.¹³ A series of

¹³ One participant obviously used a statistical calculator, as he generated a very accurate model and reported its R^2 on his experimental materials. Results are not affected by the inclusion or exclusion of this participant's responses. In this task setting, the data set was small enough that complete testing of a multiple regression model was relatively easy, and the loss of efficiency caused by including all possible predictors was minimal. As noted above, the use of calculation aids will help individuals examine relations

follow-up questions included manipulation checks, GPA in accounting and statistics courses, questions about beliefs about the relationships among costs, and questions about participants' reasoning for examining particular relationships among costs.

Experimental parameters

Within each sign condition, all data sets were statistically identical. I first generated standardized data that fit the data requirements for the research design. I then linearly transformed the standardized data to generate plausible levels of costs. The transformations were such that the means, variances and ranges of the two predictive costs (inspection and supervision) were identical to each other, thus eliminating any concerns about scale. The four columns of predictors were identical across experimental conditions; they differed only in their placement among cost pools.¹⁴ The only differences across any conditions were the values of spoilage, which differed between the negative and positive conditions by the use of a different linear transformation. Further, there were no statistically significant differences for the four predictor costs between the learning and judgment data sets. Thus, there is no concern about nonlinear relationships between spoilage and other costs due to mean differences between learning and judgment data.¹⁵ Parameters are described in Table 2.

accurately and apply their decision models consistently. However, an important step in assuring accurate estimation is the choice of relationships to examine. The use of a calculation aid will not necessarily help in this part of the task.

¹⁴ The predictive costs were always two columns away from spoilage, to control for any effects of proximity on judgment.

¹⁵ If means were different across learning and judgment data, participants might have assumed and applied nonlinear models, which would not be adequately captured by my linear modeling technique. This would result in inaccurate measures of their judgments.

Table 2: Experimental parameters

Predictor	Dataset	Mean	P value of t-test for mean difference	Std. Deviation	P value of Levene's test for s.d. difference
Stronger	Learning	38,595	0.719	15,457	0.482
	Judgment	36,915		13,756	
Weaker	Learning	38,480	0.702	11,345	0.177
	Judgment	36,880		14,713	
Zero Coefficient	Learning	26,860	0.251	3,170	0.307
Within-pool	Judgment	28,195		4,022	
Zero Coefficient	Learning	15,475	0.202	2,763	0.189
Across-pool	Judgment	14,460		2,134	

Environmental model: Spoilage = Constant \pm 1.01*Stronger \pm 0.46*Weaker
where Constant = -\$24,125 in the positive condition and \$104,125 in the negative condition

Note: I use Levene's test because the underlying data are known to be non-normal, and the F-test is sensitive to departures from normality.

This table demonstrates that the data used for the learning data sets are not statistically significantly different from those in the judgment data set.

Measurement of variables

By regressing participants' predictions of the target on the levels of the predictors, I estimate their implicit coefficients on each predictor.¹⁶ I then estimate participants' implicit coefficient errors by subtracting the environmental coefficients from the implicit coefficients. Each participant's judgment model has a constant and coefficients for each of the four costs. I chose to treat an implicit coefficient as non-zero if it was significant at

¹⁶ I assume participants use a linear, additive model because the model used to generate the experimental data is linear and additive. Further, evidence from psychology research (Brehmer 1974; Dawes and Corrigan 1974) indicates that individuals typically use linear, additive models in subjective judgment.

$p < 0.10$; otherwise I treated the implicit coefficient as zero.¹⁷ Thus, my models of participants' judgments include up to four coefficients. I also estimate the optimal or environmental model from the learning data set and generate the environmental coefficients, which represent the optimal coefficients participants could estimate. I compare participants' implicit coefficients to the environmental coefficients as described below.

To measure for an effect of overhead cost pool classification on *bias* (that is, differences between participants' within-pool and across-pool estimation errors) for Hypotheses 1 and 2, I compute a directional error difference measure equaling the signed error (negative signed error) on each coefficient when relationships are positive (negative). Thus, coefficients whose magnitudes are overestimated (underestimated) will have positive (negative) directional error, regardless of the sign of the relationships in the data. I then subtract the within-pool directional error from the across-pool directional error to create the directional error difference variables. I do this for the costs with non-zero coefficients for H1 and the costs with zero coefficients for H2 (*DirCE* and *DirZeroCE*, respectively). If either variable is negative (positive) and statistically significant, participants have on average underestimated (overestimated) across-pool coefficients more than within-pool coefficients. To test for an effect of overhead cost pool classification on *variation* for Hypotheses 1 and 2, I use the variance of the within-pool and across-pool coefficient errors.

I also estimate repeated-measure ANOVAs, treating the difference between within-pool and across-pool coefficients as a within-participant effect and the two cost

¹⁷ My results are unaffected by alternative cutoff choices of 0.05 and 0.15.

behavior manipulations (location of stronger predictor and sign) as between-participant effects. I then use the ANOVA to generate statistics describing whether the within-participant effect varies across the cost behavior conditions.

For judgment accuracy in Hypothesis 3, I use several measures to test for differences in accuracy and explore reasons for those differences in accuracy. The main measure I use is the mean squared error of participants' predictions compared to optimal predictions made by the environmental model.¹⁸ I also use three measures derived from the lens model to investigate how different sources of judgment error affect overall prediction accuracy.¹⁹ *Matching* is the correlation between the predictions made by the environmental model and predictions made by each participant's model. Matching measures how accurately participants estimated the relative values of the coefficients for the four predictors. *Consistency* is the correlation between participants' predictions and the predictions made by their model. Consistency measures how consistently participants applied their implicit models. A final measure I use is *consensus*, or the averaged correlations of participants' predictions with predictions of other participants in the same experimental condition. Consensus is not a measure of individual accuracy but rather a measure of the similarity of participants' predictions to each other. However, this measure is important because low levels of consensus imply costly disagreement among individuals and reduced likelihood of reaching agreement about judgments and their effects on organization performance.

¹⁸ Use of mean absolute error does not affect results.

¹⁹ Lens model studies typically include *achievement* as well, which is the correlation between participants' predictions and actual outcomes. Achievement is the product of three factors: matching, consistency and environmental predictability. In my study, environmental predictability is constant across conditions and is very close to its maximum value of 1.0; therefore, achievement is a redundant measure of judgment accuracy. For parsimony, I omit achievement from my study.

IV. RESULTS

Six participants from the final sample of 78 participants failed the post-task manipulation check question that asked them to identify which cost pool contained each of the five costs (the four predictors and spoilage). The failure of a post-task manipulation check may be due to failure of memory rather than one of attention or understanding. Further, the failure to recall the label on the overhead cost pool does not necessarily mean that the participant did not understand which individual cost accounts were classified together within each pool. Therefore, I retain the responses of the participants who failed the manipulation check; results are unchanged by the exclusion of these participants' data. Self-reported accounting and statistics GPA did not significantly affect any dependent variable or interact with any independent variable to affect any dependent variable ($p < 0.10$), and so are excluded from all analyses.

I also perform manipulation checks to ensure that participants attended to the cost behavior manipulations. I examine whether participants' implicit coefficients on the stronger predictor were larger than those on the weaker predictor, and whether participants' implicit coefficients carried the appropriate sign. Table 3 shows results of these manipulation checks. Panel A presents subjective coefficients for the non-zero predictors across the two sign conditions.²⁰ Data are consistent with participants placing more weight on stronger predictors than on weaker predictors and implicitly identifying the signs of coefficients accurately.

²⁰ Evidence on implicit coefficients on zero-correlation predictors is found in test of Hypotheses 1 and 2.

Table 3: Manipulation checks***Panel A: Participants' coefficients***

Sign		Stronger predictor	Weaker predictor
Positive	Mean	0.65	0.14
	N	41	41
	Std. Deviation	0.41	0.33
Negative	Mean	-0.65	-0.06
	N	37	37
	Std. Deviation	0.81	0.36

This panel shows the mean implicit coefficients on non-zero predictors in participants' subjective prediction models by sign condition.

Panel B: T-tests

Sign	Comparison	Mean	Std. Error Mean	t	df	Sig. (2-tailed)
Positive	Stronger predictor - Weaker predictor	0.52	0.10	5.378	40	0.000
Negative	Stronger predictor - Weaker predictor	-0.59	0.09	-6.00	36	0.000

This panel shows t-tests for differences between participants' implicit coefficients to test whether participants attended to data.

Panel B of Table 3 presents t-tests for mean differences between implicit coefficients on stronger and weaker predictors. Results in Panel B confirm that participants placed significantly more weight on stronger predictors than weaker predictors in both positive and negative conditions (p-values for nonzero < 0.001 for both signs). Thus, the results indicate that participants did not simply weight within-pool predictors and ignore across-pool predictors; rather, their pattern of weights indicates they paid attention to the relationships in the learning data set.

Hypotheses 1 and 2

Hypotheses 1 and 2 predicted that participants will estimate within-pool implicit coefficients more accurately than across-pool implicit coefficients for non-zero and zero predictors, respectively. Panel A of Table 4 present tests for bias. The first row presents results for Hypothesis 1. Participants underweighted across-pool non-zero predictors more than within-pool non-zero predictors, consistent with beliefs that costs assigned within pools are more likely to be strongly related than are costs assigned into different pools. *DirCE* is significantly negative (mean = -0.18, $p = 0.005$). Thus, Hypothesis 1 is supported for bias. Results for Hypothesis 2 are shown in the second row of Panel A of Table 4. Participants did not implicitly overweight within-pool zero coefficients more than across-pool coefficients. *DirZeroCE* is not significantly different from zero (mean = 0.01, $p = 0.917$). Hypothesis 2 is not supported for bias.

Panel B of Table 4 presents tests of Hypotheses 1 and 2 for variation. The variances of across-pool and within-pool non-zero predictors' coefficient errors are not statistically significantly different ($F = 1.01$; $p = 0.484$). Thus, Hypothesis 1 is supported for variation. For zero predictors' coefficients, the variance of the within-pool coefficient errors is significantly greater than that of the across-pool coefficient errors ($F = 1.61$; $p = 0.019$). Thus, Hypothesis 2 is not supported for variation.

Table 4: Hypotheses 1 and 2**Panel A: Bias**

H	Coefficient type	n			Dependent variable (A) – (B) = (C)	Paired samples t-value	Sig. (2-tailed)
			(A) Mean across-pool implicit coefficient estimation error	(B) Mean within-pool implicit coefficient estimation error	Mean difference (across-pool minus within- pool)		
1	Non-zero	78	-0.45	-0.27	-0.18	2.867	0.005
2	Zero	78	0.12	0.11	0.01	-0.104	0.917

This panel presents descriptive detail and differences for the measures used to test Hypotheses 1 and 2. Columns A and B present mean across-pool and within-pool implicit coefficient errors, respectively. Column C presents the difference between across-pool and within-pool implicit coefficient errors. The differences presented in column C are the dependent variables of interest used in testing Hypotheses 1 and 2.

Panel B: Variation

Hypothesis	Coefficient type	n			Variance ratio	Sig. (2-tailed)
			(A) Across-pool implicit coefficient estimation error variance	(B) Within-pool implicit coefficient estimation error variance		
1	Non-zero	78	0.172	0.171	1.01	0.484
2	Zero	78	0.362	0.584	1.61	0.019

This panel presents descriptive detail and differences for the measures used to test Hypotheses 1 and 2. Columns A and B present mean across-pool and within-pool implicit coefficient error variances, respectively. Column C presents the difference between across-pool and within-pool implicit coefficient error variances. The differences presented in column C are the dependent variables of interest used in testing Hypotheses 1 and 2.

Directional error is the signed error (opposite of signed error) for participants in the positive (negative) condition. Positive (negative) directional error indicates overweighting (underweighting). Non-zero (zero) coefficient indicates that the errors represented in the row are implicit coefficient errors on predictors with non-zero (zero) environmental coefficients relating the predictor to the target cost.

Taken together, the results for Hypothesis 1 support the hypothesis for both bias and variation. Thus, I conclude that for non-zero predictors, judgment accuracy is higher for within-pool coefficients than for across-pool coefficients. That is, within-pool coefficients are estimated with less bias and no more variation than across-pool coefficients. Taken together, the results for Hypothesis 2 do not support the hypothesis for either bias or variation. Thus, I conclude that for zero-correlation predictors, judgment accuracy is not higher for within-pool coefficients than for across-pool coefficients. Specifically, bias is not statistically significantly different, and variation is higher for within-pool coefficients than for across-pool coefficients.

Tests in Table 4 average results across the cost behavior conditions. It is possible that support for Hypothesis 1 is not invariant to the cost behavior condition; that is, it is possible that the effect of overhead cost pool classification on judgment is significantly different in one cost behavior condition than in the other conditions. To examine whether this is the case, I estimate a mixed-design ANOVA. The within-participant effects are the differences between the across-pool implicit coefficient estimation error and the within-pool implicit coefficient estimation error for both the nonzero and the zero-correlation predictors. The between-participant effects are the two manipulations of the relationships in the data (location of stronger predictor and sign).

I use planned contrasts to generate statistics describing whether the within-participant effect in a particular cost behavior condition varies from the mean within-participant effect in the other three cost behavior conditions.^{21,22} Note that a finding that

²¹ An alternative test would be to split my sample by cost behavior condition and test for a statistically significant effect of overhead cost pool classification within each condition. The sample is too small to allow reasonable power for such a test.

the within-participant effect in one condition does not vary from the mean effect in other conditions is the confirmation of a null hypothesis. Given my relatively small sample size, this test is not a reliable indicator of a lack of a difference across conditions. Further, I have no theoretical basis for hypothesizing a difference among cost behavior conditions. Thus, I treat these contrast tests as exploratory.

Untabulated results indicate the within-participant effects from the mixed ANOVA are identical to the t-tests presented in Table 4, as expected. Table 5 presents the results of the planned contrasts for non-zero predictors. None of the planned contrast results was significant, and partial eta-squared values for the contrasts are small (all values < 0.01). Taken together, the above contrast test results provide no evidence that the effect of overhead cost pool classification varies across the four data conditions I examined.

Hypothesis 3

Hypothesis 3 states an expectation that participants' prediction accuracy is a result of the interaction between the two manipulations of cost behavior (location of stronger relationship and sign), such that the stronger predictor being across pools will reduce overhead cost prediction accuracy more when relationships between the predictors and the target are negative than when they are positive. As noted above, I use four measures of accuracy. Table 6, Panel A presents descriptive statistics for the measures of accuracy. Cell-by-cell examination indicates accuracy is affected by the interaction of the cost behavior conditions as hypothesized. The decrease in accuracy between the across-pool

²² Because there are four data conditions, there are three degrees of freedom, and one of the four contrasts is redundant. However, because I am not making inferences from the contrast tests, the potential for inflated Type I error is not problematic. Also, I have no theoretical basis for excluding any of the four contrasts. Therefore, I include all four contrasts for completeness of presentation.

and within-pool measures of accuracy is greater for the negative condition than for the positive condition.

Table 5: Sensitivity analysis: across-pool minus within-pool implicit coefficient errors by cost behavior condition: Each cost behavior condition contrasted with the mean of the other three cost behavior conditions

Between-participant condition (location of stronger predictor, sign) compared to the mean of the other three conditions	Contrast estimate	Standard error	Sig.	Partial eta squared
Within-pool, positive	-0.24	0.45	0.596	0.004
Across-pool, positive	0.13	0.45	0.779	0.001
Within-pool, negative	0.16	0.46	0.728	0.002
Across-pool, negative	-0.05	0.47	0.913	0.000

This table shows the result of specified contrast tests for a mixed ANOVA. The within-participants effect is the directional implicit coefficient estimation error for the across-pool predictor minus the directional implicit coefficient estimation error for the within-pool predictor. The between-participants effects are the two manipulations of location of stronger predictor and sign of relationships.

Directional error is the signed error (opposite of signed error) for participants in the positive (negative) condition. Positive (negative) directional error indicates implicit overweighting (underweighting) of a predictor.

The contrast estimate is the result for a contrast that specifies the difference between the mean of the within-participant effect for the cost behavior condition and the mean of the within-participant effects for all other data conditions.

Table 6: Hypothesis 3
Panel A: Descriptive statistics

	Sign	Stronger Predictor	Mean	Std. Deviation	N
Mean Squared Error	Positive	Within pool	223,234,087	212,028,568	21
		Across pools	169,395,071	136,904,061	20
		Total	196,971,152	179,229,418	41
	Negative	Within pool	226,601,499	277,416,666	19
		Across pools	367,097,536	296,452,145	18
		Total	294,950,922	291,631,408	37
	Total	Within pool	224,833,607	242,027,520	40
		Across pools	263,043,607	244,972,613	38
		Total	243,448,735	242,642,256	78
Matching	Positive	Within pool	.75	.36	21
		Across pools	.84	.18	20
		Total	.79	.29	41
	Negative	Within pool	.76	.40	19
		Across pools	.36	.67	18
		Total	.56	.58	37
	Total	Within pool	.75	.38	40
		Across pools	.61	.53	38
		Total	.68	.46	78
Consistency	Positive	Within pool	.85	.22	21
		Across pools	.85	.14	20
		Total	.85	.18	41
	Negative	Within pool	.82	.25	19
		Across pools	.65	.42	18
		Total	.74	.35	37
	Total	Within pool	.84	.23	40
		Across pools	.75	.32	38
		Total	.80	.28	78
Consensus	Positive	Within pool	.48	.32	21
		Across pools	.52	.16	20
		Total	.50	.25	41
	Negative	Within pool	.49	.20	19
		Across pools	.12	.28	18
		Total	.31	.30	37
	Total	Within pool	.48	.26	40
		Across pools	.33	.30	38
		Total	.41	.29	78

Sign is the sign of relationships among costs.

StrongPredictor refers to the location of the stronger relationship.

Mean squared error is the mean squared error of participants' predictions compared to optimal predictions.

Matching is the correlation between the predictions made by the environmental model and predictions made by the participants' model.

Consistency is the correlation between participants' predictions and the predictions made by their model.

Consensus is the averaged correlations of participants' predictions with predictions of other participants in the same experimental condition.

Table 6: Hypothesis 3, continued
Panel B: Multivariate ANOVA

Effect	Wilks' Lambda	F(a)	Hypothesis df	Error df	Sig.
Intercept	0.03	552.23	4	71	0.000
Sign	0.84	3.281	4	71	0.016
StrongPredictor	0.86	2.87	4	71	0.029
Sign * StrongPredictor	0.85	3.17	4	71	0.019

a Exact statistic

This panel presents the results of a MANOVA, with the following variables:

Independent variables:

Sign is the sign of relationships among costs.

StrongPredictor refers to the location of the stronger relationship.

Dependent variables:

Mean squared error is the MSE of participants' predictions compared to predictions derived from the environmental model.

Matching is the correlation between the predictions made by the environmental model and predictions made by the participants' model.

Consistency is the correlation between participants' predictions and the predictions made by their model.

Consensus is the averaged correlations of participants' predictions with predictions of other participants in the same experimental condition.

Table 6: Hypothesis 3, continued
Panel C: Individual ANOVAs

Source	Dependent Variable	Mean Square	F	Sig.
Corrected Model	Mean Squared Error	1.33E+17	2.380	.076
	Matching	.856	4.581	.005
	Consistency	.177	2.415	.073
	Consensus	.637	10.477	.000
Intercept	Mean Squared Error	4.73E+17	84.604	.000
	Matching	35.388	189.326	.000
	Consistency	48.811	664.833	.000
	Consensus	12.603	207.276	.000
Sign	Mean Squared Error	1.96E+17	3.516	.065
	Matching	1.072	5.736	.019
	Consistency	.268	3.652	.060
	Consensus	.737	12.115	.001
StrongPredictor	Mean Squared Error	3.65E+16	.653	.422
	Matching	.458	2.452	.122
	Consistency	.154	2.096	.152
	Consensus	.520	8.553	.005
Sign * StrongPredictor	Mean Squared Error	1.84E+17	3.284	.074
	Matching	1.167	6.243	.015
	Consistency	.134	1.826	.181
	Consensus	.755	12.409	.001
Error	Mean Squared Error	5.59E+16		
	Matching	.187		
	Consistency	.073		
	Consensus	.061		

See Panel B for variable descriptions.

Panel B shows multivariate results of a MANOVA on the four measures of accuracy. As a group, they are significantly affected by the interaction of the location of stronger predictor and sign conditions ($p = 0.019$). Panel C shows the individual ANOVAs for each accuracy measure; all except consistency are significantly affected by the interaction (p values ≤ 0.075 ; p value for consistency = 0.181). Thus, H3 is partially supported. Note that Panel C of Table 6 indicates significant main effects of location of stronger predictor and sign on several measures of accuracy; however, due to the presence of the significant interaction effect, I do not interpret the main effects.

Interpretation of the results of Hypotheses 3 is as follows. For participants for whom the stronger predictor was across pools, those in the negative condition exhibited lower prediction accuracy than those in the positive condition. As revealed by their lower *matching* score, participants in this condition implicitly estimate the relative coefficients less accurately, indicating that their predictions result from less well-specified models. Thus, their predictions vary more from the optimal predictions, as indicated by higher *mean squared error*.²³ Finally, the participants in this cell use models that differ from each other more than those in other cells, as indicated by their lower levels of *consensus*.

Supplemental analysis

The above analysis demonstrates that overhead cost pool classification affects participants' estimation of implicit coefficients relating costs within and across pools, and the accuracy of their judgments of costs that result from their estimations. However, the results above do not specifically address *why* the effect occurs. Thus, I include analysis of experimental follow-up questions that provide some evidence on the question of why overhead cost pool classification affects coefficient estimation performance and judgment accuracy. Because these results rely on retrospective self-reports of cognitive processes, which have come under scrutiny and are commonly viewed as suspect (e.g., Nisbett and Wilson 1977), these results are considered supplementary.

Table 7, Panel A presents the follow-up questions, which are intended to elicit responses from participants as to both *how* and *why* the overhead cost pool classification affected their estimation and prediction accuracy. Participants were asked to think about

²³ The interaction is not significant for *consistency* ($p = 0.181$) but is directionally consistent with predictions. Because participants were allowed to use calculators, they should have been able to apply their implicit coefficients equally consistently across cells. High levels of consistency are therefore to be expected across all experimental conditions if participants explicitly identified relationships and applied them using calculators.

how they estimated the relationships, and then to allocate 100 points among six possible descriptions of their estimation strategies. Item C is intended to capture the likely beliefs that costs within pools are strongly correlated. Other items are intended to capture likely alternative beliefs and other foci of attention that may have resulted from the various conditions.

Mean points allocated to each item are shown in Panel A. Item C received more points than did any other item, indicating that on average, participants considered overhead cost pool classification an important factor in their cost prediction strategy because overhead cost pool classification likely describes overhead cost behavior. The difference between points allocated to Item C points allocated to all other items except Item A is statistically significant (Item A $p = 0.917$, all other p 's < 0.001). Note that item B, which offers responsibility accounting as an alternative reason for attending to overhead cost pool classification, received fewer points than did item C ($p = 0.001$, untabulated result).

It is not necessary that Item C receive significantly more points than any other item (and that the within-pool relationship receive strictly more attention than any other relationship) in order to support the hypothesis development in Chapter 2. It is sufficient that some participants allocate a non-trivial amount of attention to the relationship and that that attention affect the accuracy of those participants' judgments. By construction, the objectively optimal strategy is to ignore the overhead cost pool classification and to use all the data independently of its pool location. Thus, any deviation from that strategy in the direction suggested by the overhead cost pool classification that reduces participants' judgment accuracy supports the hypothesis.

Table 7: Supplementary analysis

Panel A: Questions

	<u>Points</u>	<u>Statement</u>
a.	26.30	I looked <i>equally</i> for relationships between spoilage and other costs <i>regardless of the cost pool</i> (that is, <i>cost pools had no effect</i> on my learning strategy) because <i>I did not expect to learn anything about the behavior of the costs from the cost pools.</i>
b.	16.35	I first looked for a relationship between spoilage and the costs in the <i>same cost pool</i> because <i>one person or group of people has responsibility for managing the costs within the pool.</i>
c.	26.78	I first looked for a relationship between spoilage and the costs in the <i>same cost pool</i> because <i>costs within the same pool are likely to have strong relationships.</i>
d.	12.57	I first looked for a relationship between spoilage and the costs in the <i>other cost pool</i> because <i>an important cause of spoilage costs is likely to be included in a different cost pool.</i>
e.	14.62	I <i>ignored all the text descriptions and cost pools</i> and <i>only used the numerical values</i> to learn about relationships between costs.
f.	<u>3.38</u>	Other.
	100.00	Total points

This panel presents follow-up questions. The entries in the points column represent mean responses (this column was blank when presented to participants).

Table 7: Supplementary analysis, continued
Panel B: Comparison of points allocation across cost behavior conditions

	Location of strong predictor	N	Mean	Std. deviation	Sig. (2-tailed)
Item A	Within pool	40	23.68	25.56	0.34
	Across pools	38	29.05	23.41	
Item B	Within pool	40	17.51	13.95	0.46
	Across pools	38	15.13	14.45	
Item C	Within pool	40	29.31	21.68	0.28
	Across pools	38	24.11	19.78	
Item D	Within pool	40	10.50	14.13	0.17
	Across pools	38	14.74	12.78	
Item E	Within pool	40	15.00	15.67	0.85
	Across pools	38	14.21	21.36	
Item F	Within pool	40	3.75	7.99	0.48
	Across pools	38	2.50	7.51	
Sign					
Item A	Positive	41	28.44	25.31	0.42
	Negative	37	23.92	23.75	
Item B	Positive	41	17.94	15.56	0.30
	Negative	37	14.59	12.38	
Item C	Positive	41	26.30	17.74	0.84
	Negative	37	27.30	24.00	
Item D	Positive	41	13.05	14.99	0.74
	Negative	37	12.03	11.99	
Item E	Positive	41	13.17	18.31	0.47
	Negative	37	16.22	18.91	
Item F	Positive	41	1.10	4.11	0.01
	Negative	37	5.41	9.96	

See Panel A for the post-experimental questions (Items A through F)

Table 7: Supplementary analysis, continued
Panel C: Correlations among points allocations and prediction errors

Strong Predictor = Within pool (n = 40)							Mean Squared Error
	Item A	Item B	Item C	Item D	Item E	Item F	
Item B	-0.34						
Item C	-0.63	0.07					
Item D	-0.26	-0.15	-0.13				
Item E	-0.15	-0.34	-0.21	-0.14			
Item F	-0.17	0.07	-0.14	-0.02	-0.08		
Mean Squared Error	-0.03	0.11	-0.15	0.19	0.01	-0.05	
Mean Absolute Error	-0.03	0.09	-0.12	0.26	-0.04	-0.12	0.97

Strong Predictor = Across pools (n = 38)							Mean Squared Error
	Item A	Item B	Item C	Item D	Item E	Item F	
Item B	-0.44						
Item C	-0.55	0.24					
Item D	-0.17	-0.24	0.00				
Item E	-0.14	-0.24	-0.48	-0.28			
Item F	-0.17	-0.07	0.04	0.10	-0.21		
Mean Squared Error	-0.30	-0.02	0.32	-0.01	0.08	-0.10	
Mean Absolute Error	-0.26	-0.07	0.28	-0.02	0.12	-0.11	0.98

Note: highlighted correlations are significant at $p < 0.05$, one-tailed

See Panel A for the post-experimental questions (Items A through F).

Mean squared error is the mean squared error of participants' predictions compared to predictions derived from the environmental model.

Mean absolute error is the mean absolute error of participants' predictions compared to predictions derived from the environmental model.

It is possible that participants' ex-post self-reported attention allocation was affected by their cost behavior condition. If this is the case, then the post-experimental

questions would not be cleanly measuring the strategies participants used initially, which should be independent of the data to which they applied the strategies. Once a participant begins to examine the data, his strategy may change as a result of the data he sees. However, my purpose with these questions is to ascertain what strategy participants *initially* used – that is, to which relationships they *initially* directed their attention. To provide evidence on whether cost behavior condition affected self-reports of attention allocation, I examine participants' responses to the questions and test for differences across data conditions. If results are not statistically significant, I will conclude that the cost behavior conditions did not affect the allocation of points, and that the responses to questions do not reflect how strategies may have been affected by the cost behavior conditions.

Table 7, Panel B shows the results of t-tests on point allocations by location of strong predictor and sign. Location of strong predictor did not affect the allocation of points to any item (all p values > 0.17). Sign only affected the allocation of points to item F ($p = 0.01$); given that the mean number of points allocated to item F in the positive (negative) condition was only 1.10 (5.40), this result is considered inconsequential to the overall analysis. Further, an untabulated MANOVA indicates that there was no interactive effect of the location of the strong predictor and sign on the points allocated to any item (all p values > 0.14). Thus, I conclude that the cost behavior conditions did not materially affect the allocation of points in the post-experimental questions.

If the overhead cost pool classification affected the allocation of participants' attention to relationships in the data, and the allocation of attention affected the accuracy of predictions, then there should be an effect of the participants' prediction strategies (as

measured by the self-reported points allocation) on the error of participants' predictions.²⁴ This effect should be conditional on the location of the stronger predictor. When the stronger predictor is within the same pool as the target, then the prediction task is relatively easy. Given the magnitude of the stronger relationship and the lack of noise in the data, even moderate attention paid to the within-pool predictor should enable participants to estimate the coefficient on the strong predictor fairly accurately. Thus, strategies that involve either looking first at the within-pool relationship (items B and C) or looking at all relationships regardless of pool location (items A and E) should be associated with lower error. A strategy of first looking at the across-pool relationship (item D), however, would lead to higher error, as participants would allocate the majority of their attention toward the weaker predictor. Thus, points allocated to items A, B, C and E should be negatively correlated with prediction error, while points allocated to item D should be positively correlated with prediction error.

Conversely, when the stronger predictor is in the opposite pool as the target, a strategy of allocation attention first to predictors within the same pool as the target and later to predictors in the other pool will result in higher error. Thus, for across-pool participants, prediction error should be positively correlated with points allocated to those items (B and C) that indicate prediction strategies that allocate attention first to predictors in the same pool as the target. A strategy of allocating attention to across-pool relationships (item D) or to all relationships regardless of pool location (items A and E) will allow participants to identify the stronger predictor in the opposite pool without first

²⁴ Untabulated results indicate that correlations among points allocated to the post-experimental questions and *DirCE* are directionally consistent with the discussion below relating strategies to overall prediction error (MSE and MAE), but are not statistically significant.

having allocated much attention to the within-pool relationship, and so points allocated to these items should be negative correlated with error.

Table 7, Panel C presents correlations among the points allocations and prediction error. For the within-pool participants, prediction error measures do not significantly correlate with points allocations. However, several of the correlations are quantitatively in the predicted direction. Correlations between both error measures and Item C are negative.²⁵ Correlations between error measures and item D are positive (for MAE $p = 0.055$; for MSE $p = 0.11$; one-tailed). Thus, those subjects whose prediction strategies included early allocation of attention to predictors with the same pool as the target (which includes the strong predictor) made predictions with less error, and those who allocated initial attention to the predictors in the other pool (including the weak predictor) made predictions with more error.

For across-pool participants, the results are somewhat stronger. Points allocated to item C are positively correlated with both error measures (p values for MSE and MAE both < 0.05) and points allocated to Item A are negatively correlated with both error measures (p value for MSE < 0.035 ; p value for MAE $= 0.059$). Thus, those subjects whose prediction strategies included early allocation of attention to predictors with the same pool as the target (which includes the weak predictor) made predictions with more error, and those who allocated initial attention to the predictors in the other pool (including the strong predictor) made predictions with less error.

²⁵ It is possible that the restricted range of points allocated to items affects the correlations. The ranges for items are: A: 100; B: 60; C: 100; D: 75; E: 80; and F: 40. Thus, items A and C, which have the greatest ranges, also have statistically significant correlations with error measures for the across-pool participants, while other items have no significant correlations.

Though the results are not consistently statistically significant, the supplemental analysis overall is consistent with the theoretical development in Chapter 2 above. The evidence is consistent with prediction error resulting in part from participants' allocation of attention among various predictors, and with participants allocating attention in part based on the classification of costs within pools.

V. DISCUSSION AND CONCLUSION

Discussion

This study provides evidence that overhead cost pool classification affects the accuracy of judgments about cost behavior by users of accounting systems. I demonstrate that while individuals do pay significant attention to the data they are given, they estimate coefficients within overhead cost pools more accurately than they do coefficients across overhead cost pools, and there is evidence consistent with the effect being robust to differences in the location of a stronger vs. a weaker predictive relationship and the sign of the coefficients. I also show that individuals underestimate the magnitude of across-pool coefficients more than they do for within-pool coefficients. This pattern is consistent with empirical evidence found in Joshi et al. (2001), in which the magnitude of relationships among costs assigned into different cost pools was underestimated by managers. While there are likely other causes for the estimation errors exhibited by managers at those firms, I have demonstrated that overhead cost pool classification is a plausible cause of the errors.

I have also shown that the accuracy of participants' cost predictions depends on an interaction between the pool location of the stronger predictive relationship and the sign of coefficients. Participants facing negative relationships between costs and stronger predictors located across cost pools exhibited greater error and lower consensus than did other participants. More broadly, my results provide evidence on tradeoffs organizations face when designing cost accounting systems. Organizations' overhead cost pool classification decisions should be informed by judgment-related effects as well as the potential for product costing errors as described by prior literature.

Contribution

I contribute to the academic and practice literature on cost system design by positing and finding evidence for a *cognitive* effect of cost system design in addition to the *information* effect previously considered (e.g., Noreen 1991; Christensen and Demski 1995, 1997). I present evidence that classification decisions affect the use of information provided by cost systems as well as the provision of the information itself. My results suggest that cost systems that separate into different cost pools those costs whose relationships are important and are estimated subjectively may hinder effective judgments and decisions by managers. Decisions such as those faced by managers of firms examined in Anderson (1995) (i.e., determining optimal production flexibility, including setup and production schedules) and Joshi et al. (2001) (i.e., determining the costs of regulation, and making various decisions not obviously affected by regulation but in a highly regulated context) may be affected by cost system design, even if managers have all the information they need. Future research can investigate these findings further; for example, researchers may endeavor to determine when classifications of accounting information are likely to have larger or smaller effects on judgment, or whether experience or instruction affects classification effects.

Further, I present evidence that the effect of overhead cost pool classification on managers' judgment performance is dependent on the sign of the relationships among costs. The effect of separating a relationship into different cost pools is greater when costs are negatively correlated (that is, when they are substitutes) than when costs are positively correlated (that is, when they are complements). This suggests that managers' judgment performance will vary depending on whether the economic environment presents positive or negative correlations. For example, managers attempting to predict

the effects of investments in training on the cost of waste (assuming these two costs are negatively correlated) may experience significant judgment failures if the costs are in different pools. Future research can investigate the boundary conditions on this interaction (e.g., how environments with mixed signs affect judgment performance, whether similar effects are noted between cost and revenue items classified separately; whether transforming negative correlations into positive correlations improves judgments).

I also contribute to practical and instructional literature on cost system design. As noted, typical textbook instruction of cost pool construction features heavy discussion of correlation-based pool construction for accurate product costing. Discussions of responsibility accounting, performance evaluation and other uses of pooled cost accounting systems are typically separated from discussions of cost system design. Practitioners and students might benefit from a more integrated approach to discussions of cost system design, including discussions of the assumptions underlying cost pool design. For example, students might be presented with “classroom experiment” in which they are given a single cost system and asked to make multiple decisions, including external reporting, product costing and performance evaluation decisions. Other students might be asked to make the same decisions for the same firm, but with a different set of cost pools. Such a task might illuminate the compromises inherent in cost systems in practice, and help mitigate the effects of the product-costing focus of cost system design instruction in classrooms. Similarly, practitioner-oriented recommendations about designing cost pools around highly correlated costs (e.g., Roth and Borthick 1991;

Kaplan and Cooper 1998) might provide balance by advising users that such cost system designs have the potential to affect users' judgments about relationships among costs.

Limitations

This study is subject to several limitations. This study used student participants in a laboratory setting. My participants generally had little work experience, and none of my participants had any experience working in the hypothetical firm or the given accounting system. Thus, there is a possibility that individuals with experience working with their firms' accounting systems would produce different results. To the extent that the results of my experiment are *not* caused by cognitive processes common to most individuals educated in basic cost accounting, or may be affected by specific experience or knowledge, my results may not be representative of managers performing familiar tasks.

Several factors provide evidence in favor of my results' generalizability. One is the fact that important across-pool relationships were grossly underestimated by experienced managers in Joshi et al. (2001). This finding provides corroborating evidence that the effects noted here exist outside the laboratory. Also, the pervasive nature of categorization noted in the psychology literature (Murphy and Medin 1985; Markman and Gentner 2001) lends support to the notion that categorization effects will occur and affect reasoning in a broad variety of circumstances. In this vein, Hopkins (1996) provides evidence that experienced financial analysts' predictions are affected by the balance-sheet classification of hybrid securities, thus corroborating the effects of classification on judgment of experienced users. Finally, Vera-Munoz et al. (2001) provide evidence that both task-specific accounting experience, not general accounting experience, and appropriate analysis formats are required for maximum task performance. If managers do not have task-specific experience making across-pool

judgments of relationships among overhead costs, general experience with accounting systems may not aid judgment.

Second, it is possible that the results are largely driven by the particular reporting format I used. That is, the reporting format presented details of pooled items separated into columns on the page, thus potentially reinforcing the pooling and adding a perceptual (that is, visual) element of classification to the conceptual element of the accounting system design. Thus, it is possible that if systems used in practice report costs in a format that does not visually reinforce the classification, the effect on managers' judgments will be reduced or will not occur at all. However, it is unlikely that many systems in practice do not visually segregate costs within classifications into portions of reports, or even report them on separate pages or reports. A primary purpose of cost pools is the segregation of costs for product costing purposes, so it is likely that reports of pooled costs will likely feature some degree of visual segregation. Future research can examine effects of various types of accounting information display of classified accounting information on judgment performance.

Finally, the mediating variable, the attention-allocation effect of overhead cost pool classification, is not well supported by my measures. It is possible the retrospective reports of strategy were ill-constructed. It is also possible that participants' attention allocation was not the only mediating variable, but there was another mediator, such as strong beliefs that certain costs have strong relationships or that cost pools are actually classified according to meaningful statistical relationships. My manipulation of the labels on costs was intended to eliminate the alternative explanation that participants had strong beliefs about relationships among certain types of costs. Given that there were no main or

interactive effects of the cost label variable, it does not seem likely that my results are driven by this alternative explanation. Further, manipulation checks reported in Table 3 indicate that participants generally attended to the data in all pools, and did not ignore across-pool relationships. The pattern of participants' implicit coefficients indicated that the participants put more weight on stronger relationships both within- and across-pools, and generally identified the signs of the relationships. This appears inconsistent with participants having strong beliefs that across-pool correlations are necessarily low. However, future research can allow for more direct measures of attention allocation as a mediator, such as process measures or eye- and gaze-tracking devices, to test this mediator more fully.

APPENDIX

[Note: this is the instrument for the following conditions: positive correlations, stronger predictor is within-pool, spoilage is in the supervisory costs pool.]

Background

Assume you are the controller of a manufacturing firm. One of the important parts of your job is to **predict future costs** as part of your firm's short-term budgeting process. One cost that you must predict for the plants in your firm is the **monthly reported spoilage cost** – that is, the cost of products that are discarded because they do not pass inspection. This cost must be predicted because it is not an amount that plant managers directly decide to spend, but is the result of things that happen during the month.

Some (not necessarily all) of the other activities at the plant influence the amount of spoilage each month. The main activities in the plant other than direct production are **inspection, testing, supervision, and training**. *Higher spending* on one (or more) of these activities could lead to *higher levels of spoilage costs* being recorded, because more care is taken to *identify and discard defective units* before they are sent to customers. No formal statistical analysis of the relationships among these costs has been performed, so it is not yet known which, if any, of the other activity costs are good predictors of spoilage costs.

The plants in your region are all comparable in terms of workforce, equipment and product mix, so the relationships, if any, between inspection, supervision, training and spoilage are very similar across plants. Also, wages and input prices are similar across plants, so differences in spending levels represent differences in activity levels, not differences in prices or wages.

In order to help you predict next month's spoilage costs, your plants' cost accountants have provided the information on **Exhibit 1** from the plants' cost accounting systems. The information includes the last month's spoilage costs. Also included in Exhibit 1 are the other costs that could be helpful in predicting spoilage costs. Last month's costs are typical for your firm, and should offer a good basis for predicting next month's costs.

Note that the firm's cost accounting system reports all these costs in two **cost pools** for each plant:

1. The **Quality Control pool** includes **inspection** and **testing** costs. This pool captures the costs of ensuring that no defective products go out to customers.
2. The **Supervision pool** includes wages and benefits for **supervisors** and the costs of **training programs**, and also **spoilage** costs. This pool captures the costs of preventing poor quality work by ensuring the line employees are well trained and have adequate supervision.

Costs within each pool are totaled, and only the pool total is regularly reported to most managers. The pool total is used to allocate costs to individual products and customers. Please examine Exhibit 1 and **learn as much as you can** about predicting spoilage costs from the other costs provided. When you are finished, please continue on to the next page.

Cost prediction

When you are finished examining Exhibit 1, please turn to **Exhibit 2**. Exhibit 2 contains partial budgets for the region's plants, as prepared by the plants' managers. The amounts included on Exhibit 2 include the monthly quality control and supervision costs the plant managers have budgeted for next month.

Based on your conversations with the cost accountants and plant managers and your review of your plants' production plans, you believe the budgeted amounts on Exhibit 2 are reasonable. You also believe that the relationships between these costs and spoilage costs are likely to be the same in the next month as they were last month.

Please use the budgeted costs on Exhibit 2 to ***predict monthly spoilage costs*** for next month based on what you have learned from Exhibit 1. Feel free to use a calculator.

It is important that you try to predict costs as accurately as possible. If your predictions are inaccurate, the firm's future profitability and your performance evaluations will suffer.

Recall also that your pay is based on your predictions. Your predictions will be compared to the best predictions that can be made from the data provided. The closer your predictions to the best possible predictions, the higher your pay will be.

The plant names on Exhibit 2 are disguised. It is not a good strategy to try to "match" one plant on Exhibit 2 with one or two plants on Exhibit 1. It is a ***better strategy*** to try to ***learn relationships among the costs*** and use these relationships to predict the spoilage costs.

Please complete the 20 spoilage cost predictions now.

Once you are finished with your predictions, please turn to the next page.

Advice to top management

Now that you have learned about the relationships among the various costs and have made your predictions, top management has asked you for your advice on a decision. Because of recent concerns about product quality, top management would like to ***increase its spending on quality-improvement initiatives***. However, top managers are unsure about how to make the greatest impact on quality-related costs. Thus, they are considering two different options. Note that these two options are ***mutually exclusive*** – that is, ***management will pursue only one of them, but not both***.

For help in deciding which option to pursue, management has asked you for an estimate of the effect of each of the two options. ***Your estimate should be based on the relationships you have learned from Exhibit 1.*** Please feel free to refer to Exhibit 1 when making these estimates.

Option 1: What would be the change in spoilage costs if management gave ***each plant an additional \$10,000 per month to spend on inspection?*** There would be no change in any other spending levels.

Each plant's monthly spoilage costs would be expected to (circle one) **increase** or **decrease** by

about \$ _____.

Option 2: What would be the change in spoilage costs if management gave ***each plant an additional \$10,000 per month to spend on supervisors?*** There would be no change in any other spending levels.

Each plant's monthly spoilage costs would be expected to (circle one) **increase** or **decrease** by

about \$ _____.

Thank you very much. Now, please ***return this packet*** to the researcher, and ***pick up your second packet***.

Exhibit 1: Plants' cost data from cost accounting system

Plant	Supervisory Costs cost pool				Quality Control cost pool			
	Supervisors	Details		Pool Total	Inspection	Details		Pool Total
		Training	Spoilage			Testing		
1	\$ 39,000	\$ 14,000	\$ 12,700	\$ 65,700	\$ 16,800	\$ 32,000	\$ 48,800	
2	46,500	18,300	25,100	89,900	28,000	23,000	51,000	
3	29,000	18,400	61,200	108,600	62,900	27,200	90,100	
4	28,000	16,200	21,700	65,900	36,400	31,300	67,700	
5	32,000	18,000	21,500	71,500	35,000	27,500	62,500	
6	59,500	12,500	60,700	132,700	58,500	26,000	84,500	
7	32,500	10,200	39,500	82,200	51,700	27,500	79,200	
8	16,900	19,000	26,800	62,700	48,500	23,100	71,600	
9	55,100	17,000	41,400	113,500	29,000	24,400	53,400	
10	36,000	19,600	47,700	103,300	49,000	28,100	77,100	
11	37,000	15,000	15,400	67,400	30,000	21,500	51,500	
12	37,300	15,900	13,600	66,800	21,600	30,600	52,200	
13	36,800	13,800	44,300	94,900	42,000	23,700	65,700	
14	50,000	18,600	53,400	122,000	56,800	24,500	81,300	
15	25,300	14,200	29,500	69,000	38,500	32,500	71,000	
16	53,600	13,000	69,300	135,900	64,300	29,100	93,400	
17	48,500	15,300	26,100	89,900	43,700	29,000	72,700	
18	37,500	10,200	15,300	63,000	22,500	25,600	48,100	
19	23,600	14,100	12,900	50,600	20,100	25,700	45,800	
20	45,500	16,200	12,700	74,400	16,600	24,900	41,500	

Exhibit 2: Plants' partial budgeted cost data

Plant	Supervisory Costs cost pool			Quality Control cost pool		
	Supervisors	Details		Inspection	Details	
		Training	Spoilage		Testing	
A	\$ 55,500	\$ 14,000		\$ 57,500	\$ 26,000	
B	23,500	16,300		35,000	32,300	
C	34,200	14,200		20,500	22,300	
D	35,000	13,000		30,000	27,900	
E	47,500	14,800		20,500	24,800	
F	39,900	15,000		40,000	30,100	
G	22,000	13,200		17,500	30,500	
H	21,500	14,500		53,000	34,200	
I	37,400	17,500		22,000	27,100	
J	33,500	11,100		30,900	27,500	
K	20,700	17,900		40,000	23,800	
L	19,000	16,800		26,900	30,200	
M	59,400	13,900		46,100	31,400	
N	18,900	10,200		45,200	29,000	
O	64,100	11,000		36,000	29,000	
P	49,000	16,800		29,600	31,300	
Q	42,500	15,000		24,200	33,700	
R	33,000	13,100		41,800	20,000	
S	58,000	16,100		64,900	21,700	
T	23,000	14,800		56,700	31,100	

[Note: this is the instrument for the following conditions: positive correlations, stronger predictor is across-pool, spoilage is in the supervisory costs pool.]

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	Supervisors	Details		Pool Total	Inspection	Details		Pool Total
		Training	Spoilage			Testing		
1	\$ 16,800	\$ 14,000	\$ 12,700	\$ 43,500	\$ 39,000	\$ 32,000	\$ 71,000	
2	28,000	18,300	25,100	71,400	46,500	23,000	69,500	
3	62,900	18,400	61,200	142,500	29,000	27,200	56,200	
4	36,400	16,200	21,700	74,300	28,000	31,300	59,300	
5	35,000	18,000	21,500	74,500	32,000	27,500	59,500	
6	58,500	12,500	60,700	131,700	59,500	26,000	85,500	
7	51,700	10,200	39,500	101,400	32,500	27,500	60,000	
8	48,500	19,000	26,800	94,300	16,900	23,100	40,000	
9	29,000	17,000	41,400	87,400	55,100	24,400	79,500	
10	49,000	19,600	47,700	116,300	36,000	28,100	64,100	
11	30,000	15,000	15,400	60,400	37,000	21,500	58,500	
12	21,600	15,900	13,600	51,100	37,300	30,600	67,900	
13	42,000	13,800	44,300	100,100	36,800	23,700	60,500	
14	56,800	18,600	53,400	128,800	50,000	24,500	74,500	
15	38,500	14,200	29,500	82,200	25,300	32,500	57,800	
16	64,300	13,000	69,300	146,600	53,600	29,100	82,700	
17	43,700	15,300	26,100	85,100	48,500	29,000	77,500	
18	22,500	10,200	15,300	48,000	37,500	25,600	63,100	
19	20,100	14,100	12,900	47,100	23,600	25,700	49,300	
20	16,600	16,200	12,700	45,500	45,500	24,900	70,400	

Exhibit 2: Plants' partial budgeted cost data

Plant	Supervisory Costs cost pool			Quality Control cost pool		
	Supervisors	Details		Inspection	Testing	
		Training	Spoilage			
A	\$ 57,500	\$ 14,000		\$ 55,500	\$ 26,000	
B	35,000	16,300		23,500	32,300	
C	20,500	14,200		34,200	22,300	
D	30,000	13,000		35,000	27,900	
E	20,500	14,800		47,500	24,800	
F	40,000	15,000		39,900	30,100	
G	17,500	13,200		22,000	30,500	
H	53,000	14,500		21,500	34,200	
I	22,000	17,500		37,400	27,100	
J	30,900	11,100		33,500	27,500	
K	40,000	17,900		20,700	23,800	
L	26,900	16,800		19,000	30,200	
M	46,100	13,900		59,400	31,400	
N	45,200	10,200		18,900	29,000	
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5	32,000	18,000	58,500	108,500	35,000	27,500	62,500	
6	59,500	12,500	19,300	91,300	58,500	26,000	84,500	
7	32,500	10,200	40,500	83,200	51,700	27,500	79,200	
8	16,900	19,000	53,200	89,100	48,500	23,100	71,600	
9	55,100	17,000	38,600	110,700	29,000	24,400	53,400	
10	36,000	19,600	32,300	87,900	49,000	28,100	77,100	
11	37,000	15,000	64,600	116,600	30,000	21,500	51,500	
12	37,300	15,900	66,400	119,600	21,600	30,600	52,200	
13	36,800	13,800	35,700	86,300	42,000	23,700	65,700	
14	50,000	18,600	26,600	95,200	56,800	24,500	81,300	
15	25,300	14,200	50,500	90,000	38,500	32,500	71,000	
16	53,600	13,000	10,700	77,300	64,300	29,100	93,400	
17	48,500	15,300	53,900	117,700	43,700	29,000	72,700	
18	37,500	10,200	64,700	112,400	22,500	25,600	48,100	
19	23,600	14,100	67,100	104,800	20,100	25,700	45,800	
20	45,500	16,200	67,300	129,000	16,600	24,900	41,500	

Exhibit 2: Plants' partial budgeted cost data

Plant	Supervisory Costs cost pool			Quality Control cost pool		
	Supervisors	Details		Inspection	Details	
		Training	Spoilage		Testing	
A	\$ 55,500	\$ 14,000		\$ 57,500	\$ 26,000	
B	23,500	16,300		35,000	32,300	
C	34,200	14,200		20,500	22,300	
D	35,000	13,000		30,000	27,900	
E	47,500	14,800		20,500	24,800	
F	39,900	15,000		40,000	30,100	
G	22,000	13,200		17,500	30,500	
H	21,500	14,500		53,000	34,200	
I	37,400	17,500		22,000	27,100	
J	33,500	11,100		30,900	27,500	
K	20,700	17,900		40,000	23,800	
L	19,000	16,800		26,900	30,200	
M	59,400	13,900		46,100	31,400	
N	18,900	10,200		45,200	29,000	
O	64,100	11,000		36,000	29,000	
P	49,000	16,800		29,600	31,300	
Q	42,500	15,000		24,200	33,700	
R	33,000	13,100		41,800	20,000	
S	58,000	16,100		64,900	21,700	
T	23,000	14,800		56,700	31,100	

[Note: this is the instrument for the following conditions: negative correlations, stronger predictor is across-pool, spoilage is in the supervisory costs pool.]

Background

Assume you are the controller of a manufacturing firm. One of the important parts of your job is to **predict future costs** as part of your firm's short-term budgeting process. One cost that you must predict for the plants in your firm is the **monthly reported spoilage cost** – that is, the cost of products that are discarded because they do not pass inspection. This cost must be predicted because it is not an amount that plant managers directly decide to spend, but is the result of things that happen during the month.

Some (not necessarily all) of the other activities at the plant influence the amount of spoilage each month. The main activities in the plant other than direct production are **inspection, testing, supervision, and training**. *Higher spending* on one (or more) of these activities could lead to *lower spoilage costs* by *improving production quality*. No formal statistical analysis of the relationships among these costs has been performed, so it is not yet known which, if any, of the other activity costs are good predictors of spoilage costs.

The plants in your region are all comparable in terms of workforce, equipment and product mix, so the relationships, if any, between inspection, supervision, training and spoilage are very similar across plants. Also, wages and input prices are similar across plants, so differences in spending levels represent differences in activity levels, not differences in prices or wages.

In order to help you predict next month's spoilage costs, your plants' cost accountants have provided the information on **Exhibit 1** from the plants' cost accounting systems. The information includes the last month's spoilage costs. Also included in Exhibit 1 are the other costs that could be helpful in predicting spoilage costs. Last month's costs are typical for your firm, and should offer a good basis for predicting next month's costs.

Note that the firm's cost accounting system reports all these costs in two **cost pools** for each plant:

3. The **Quality Control pool** includes **inspection** and **testing** costs. This pool captures the costs of ensuring that no defective products go out to customers.
4. The **Supervision pool** includes wages and benefits for **supervisors** and the costs of **training programs**, and also **spoilage** costs. This pool captures the costs of preventing poor quality work by ensuring the line employees are well trained and have adequate supervision.

Costs within each pool are totaled, and only the pool total is regularly reported to most managers. The pool total is used to allocate costs to individual products and customers.

Please examine Exhibit 1 and **learn as much as you can** about predicting spoilage costs from the other costs provided. When you are finished, please continue on to the next page.

Cost prediction

When you are finished examining Exhibit 1, please turn to **Exhibit 2**. Exhibit 2 contains partial budgets for the region's plants, as prepared by the plants' managers. The amounts included on Exhibit 2 include the monthly quality control and supervision costs the plant managers have budgeted for next month.

Based on your conversations with the cost accountants and plant managers and your review of your plants' production plans, you believe the budgeted amounts on Exhibit 2 are reasonable. You also believe that the relationships between these costs and spoilage costs are likely to be the same in the next month as they were last month.

Please use the budgeted costs on Exhibit 2 to ***predict monthly spoilage costs*** for next month based on what you have learned from Exhibit 1. Feel free to use a calculator.

It is important that you try to predict costs as accurately as possible. If your predictions are inaccurate, the firm's future profitability and your performance evaluations will suffer.

Recall also that your pay is based on your predictions. Your predictions will be compared to the best predictions that can be made from the data provided. The closer your predictions to the best possible predictions, the higher your pay will be.

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Please complete the 20 spoilage cost predictions now.

Once you are finished with your predictions, please turn to the next page.

Advice to top management

Now that you have learned about the relationships among the various costs and have made your predictions, top management has asked you for your advice on a decision. Because of recent concerns about product quality, top management would like to ***increase its spending on quality-improvement initiatives***. However, top managers are unsure about how to make the greatest impact on quality-related costs. Thus, they are considering two different options. Note that these two options are ***mutually exclusive*** – that is, ***management will pursue only one of them, but not both***.

For help in deciding which option to pursue, management has asked you for an estimate of the effect of each of the two options. ***Your estimate should be based on the relationships you have learned from Exhibit 1.*** Please feel free to refer to Exhibit 1 when making these estimates.

Option 1: What would be the change in spoilage costs if management gave ***each plant an additional \$10,000 per month to spend on inspection?*** There would be no change in any other spending levels.

Each plant's monthly spoilage costs would be expected to (circle one) **increase** or **decrease** by

about \$ _____.

Option 2: What would be the change in spoilage costs if management gave ***each plant an additional \$10,000 per month to spend on supervisors?*** There would be no change in any other spending levels.

Each plant's monthly spoilage costs would be expected to (circle one) **increase** or **decrease** by

about \$ _____.

Thank you very much. Now, please ***return this packet*** to the researcher, and ***pick up your second packet***.

Exhibit 1: Plants' cost data from cost accounting system

Plant	Supervisory Costs cost pool				Quality Control cost pool			
	Supervisors	Details		Pool Total	Inspection	Details		Pool Total
		Training	Spoilage			Testing		
1	\$ 16,800	\$ 14,000	\$ 67,300	\$ 98,100	\$ 39,000	\$ 32,000	\$ 71,000	
2	28,000	18,300	54,900	101,200	46,500	23,000	69,500	
3	62,900	18,400	18,800	100,100	29,000	27,200	56,200	
4	36,400	16,200	58,300	110,900	28,000	31,300	59,300	
5	35,000	18,000	58,500	111,500	32,000	27,500	59,500	
6	58,500	12,500	19,300	90,300	59,500	26,000	85,500	
7	51,700	10,200	40,500	102,400	32,500	27,500	60,000	
8	48,500	19,000	53,200	120,700	16,900	23,100	40,000	
9	29,000	17,000	38,600	84,600	55,100	24,400	79,500	
10	49,000	19,600	32,300	100,900	36,000	28,100	64,100	
11	30,000	15,000	64,600	109,600	37,000	21,500	58,500	
12	21,600	15,900	66,400	103,900	37,300	30,600	67,900	
13	42,000	13,800	35,700	91,500	36,800	23,700	60,500	
14	56,800	18,600	26,600	102,000	50,000	24,500	74,500	
15	38,500	14,200	50,500	103,200	25,300	32,500	57,800	
16	64,300	13,000	10,700	88,000	53,600	29,100	82,700	
17	43,700	15,300	53,900	112,900	48,500	29,000	77,500	
18	22,500	10,200	64,700	97,400	37,500	25,600	63,100	
19	20,100	14,100	67,100	101,300	23,600	25,700	49,300	
20	16,600	16,200	67,300	100,100	45,500	24,900	70,400	

Exhibit 2: Plants' partial budgeted cost data

Plant	Supervisory Costs cost pool			Quality Control cost pool		
	Supervisors	Details		Inspection	Testing	
		Training	Spoilage			
A	\$ 57,500	\$ 14,000		\$ 55,500	\$ 26,000	
B	35,000	16,300		23,500	32,300	
C	20,500	14,200		34,200	22,300	
D	30,000	13,000		35,000	27,900	
E	20,500	14,800		47,500	24,800	
F	40,000	15,000		39,900	30,100	
G	17,500	13,200		22,000	30,500	
H	53,000	14,500		21,500	34,200	
I	22,000	17,500		37,400	27,100	
J	30,900	11,100		33,500	27,500	
K	40,000	17,900		20,700	23,800	
L	26,900	16,800		19,000	30,200	
M	46,100	13,900		59,400	31,400	
N	45,200	10,200		18,900	29,000	
O	36,000	11,000		64,100	29,000	
P	29,600	16,800		49,000	31,300	
Q	24,200	15,000		42,500	33,700	
R	41,800	13,100		33,000	20,000	
S	64,900	16,100		58,000	21,700	
T	56,700	14,800		23,000	31,100	

[Note: this is the instrument for the following conditions: positive correlations, stronger predictor is within-pool, spoilage is in the quality control costs pool.]

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Exhibit 1: Plants' cost data from cost accounting system

Plant	Quality Control cost pool				Supervisory Costs cost pool			
	Inspection	Details		Pool Total	Supervisors	Details		Pool Total
		Testing	Spoilage			Training		
1	\$ 39,000	\$ 14,000	\$ 12,700	\$ 65,700	\$ 16,800	\$ 32,000	\$ 48,800	
2	46,500	18,300	25,100	89,900	28,000	23,000	51,000	
3	29,000	18,400	61,200	108,600	62,900	27,200	90,100	
4	28,000	16,200	21,700	65,900	36,400	31,300	67,700	
5	32,000	18,000	21,500	71,500	35,000	27,500	62,500	
6	59,500	12,500	60,700	132,700	58,500	26,000	84,500	
7	32,500	10,200	39,500	82,200	51,700	27,500	79,200	
8	16,900	19,000	26,800	62,700	48,500	23,100	71,600	
9	55,100	17,000	41,400	113,500	29,000	24,400	53,400	
10	36,000	19,600	47,700	103,300	49,000	28,100	77,100	
11	37,000	15,000	15,400	67,400	30,000	21,500	51,500	
12	37,300	15,900	13,600	66,800	21,600	30,600	52,200	
13	36,800	13,800	44,300	94,900	42,000	23,700	65,700	
14	50,000	18,600	53,400	122,000	56,800	24,500	81,300	
15	25,300	14,200	29,500	69,000	38,500	32,500	71,000	
16	53,600	13,000	69,300	135,900	64,300	29,100	93,400	
17	48,500	15,300	26,100	89,900	43,700	29,000	72,700	
18	37,500	10,200	15,300	63,000	22,500	25,600	48,100	
19	23,600	14,100	12,900	50,600	20,100	25,700	45,800	
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Exhibit 2: Plants' partial budgeted cost data

Plant	Quality Control cost pool			Supervisory Costs cost pool		
	Details			Details		
	Inspection	Testing	Spoilage	Supervisors	Training	
A	\$ 55,500	\$ 14,000		\$ 57,500	\$ 26,000	
B	23,500	16,300		35,000	32,300	
C	34,200	14,200		20,500	22,300	
D	35,000	13,000		30,000	27,900	
E	47,500	14,800		20,500	24,800	
F	39,900	15,000		40,000	30,100	
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J	33,500	11,100		30,900	27,500	
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		Testing	Spoilage			Training		
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3	62,900	18,400	61,200	142,500	29,000	27,200	56,200	
4	36,400	16,200	21,700	74,300	28,000	31,300	59,300	
5	35,000	18,000	21,500	74,500	32,000	27,500	59,500	
6	58,500	12,500	60,700	131,700	59,500	26,000	85,500	
7	51,700	10,200	39,500	101,400	32,500	27,500	60,000	
8	48,500	19,000	26,800	94,300	16,900	23,100	40,000	
9	29,000	17,000	41,400	87,400	55,100	24,400	79,500	
10	49,000	19,600	47,700	116,300	36,000	28,100	64,100	
11	30,000	15,000	15,400	60,400	37,000	21,500	58,500	
12	21,600	15,900	13,600	51,100	37,300	30,600	67,900	
13	42,000	13,800	44,300	100,100	36,800	23,700	60,500	
14	56,800	18,600	53,400	128,800	50,000	24,500	74,500	
15	38,500	14,200	29,500	82,200	25,300	32,500	57,800	
16	64,300	13,000	69,300	146,600	53,600	29,100	82,700	
17	43,700	15,300	26,100	85,100	48,500	29,000	77,500	
18	22,500	10,200	15,300	48,000	37,500	25,600	63,100	
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	Details			Details		
	Inspection	Testing	Spoilage	Supervisors	Training	
A	\$ 57,500	\$ 14,000		\$ 55,500	\$ 26,000	
B	35,000	16,300		23,500	32,300	
C	20,500	14,200		34,200	22,300	
D	30,000	13,000		35,000	27,900	
E	20,500	14,800		47,500	24,800	
F	40,000	15,000		39,900	30,100	
G	17,500	13,200		22,000	30,500	
H	53,000	14,500		21,500	34,200	
I	22,000	17,500		37,400	27,100	
J	30,900	11,100		33,500	27,500	
K	40,000	17,900		20,700	23,800	
L	26,900	16,800		19,000	30,200	
M	46,100	13,900		59,400	31,400	
N	45,200	10,200		18,900	29,000	
O	36,000	11,000		64,100	29,000	
P	29,600	16,800		49,000	31,300	
Q	24,200	15,000		42,500	33,700	
R	41,800	13,100		33,000	20,000	
S	64,900	16,100		58,000	21,700	
T	56,700	14,800		23,000	31,100	

[Note: this is the instrument for the following conditions: negative correlations, stronger predictor is within-pool, spoilage is in the quality control costs pool.]

Background

Assume you are the controller of a manufacturing firm. One of the important parts of your job is to **predict future costs** as part of your firm's short-term budgeting process. One cost that you must predict for the plants in your firm is the **monthly reported spoilage cost** – that is, the cost of products that are discarded because they do not pass inspection. This cost must be predicted because it is not an amount that plant managers directly decide to spend, but is the result of things that happen during the month.

Some (not necessarily all) of the other activities at the plant influence the amount of spoilage each month. The main activities in the plant other than direct production are **inspection, testing, supervision, and training**. *Higher spending* on one (or more) of these activities could lead to *lower spoilage costs* by *improving production quality*. No formal statistical analysis of the relationships among these costs has been performed, so it is not yet known which, if any, of the other activity costs are good predictors of spoilage costs.

The plants in your region are all comparable in terms of workforce, equipment and product mix, so the relationships, if any, between inspection, supervision, training and spoilage are very similar across plants. Also, wages and input prices are similar across plants, so differences in spending levels represent differences in activity levels, not differences in prices or wages.

In order to help you predict next month's spoilage costs, your plants' cost accountants have provided the information on **Exhibit 1** from the plants' cost accounting systems. The information includes the last month's spoilage costs. Also included in Exhibit 1 are the other costs that could be helpful in predicting spoilage costs. Last month's costs are typical for your firm, and should offer a good basis for predicting next month's costs.

Note that the firm's cost accounting system reports all these costs in two **cost pools** for each plant:

1. The **Quality Control pool** includes **inspection, testing** and **spoilage** costs. This pool captures the costs of ensuring that no defective products go out to customers.
2. The **Supervision pool** includes wages and benefits for **supervisors** and the costs of **training programs**. This pool captures the costs of preventing poor quality work by ensuring the line employees are well trained and have adequate supervision.

Costs within each pool are totaled, and only the pool total is regularly reported to most managers. The pool total is used to allocate costs to individual products and customers.

Please examine Exhibit 1 and **learn as much as you can** about predicting spoilage costs from the other costs provided. When you are finished, please continue on to the next page.

Cost prediction

When you are finished examining Exhibit 1, please turn to **Exhibit 2**. Exhibit 2 contains partial budgets for the region's plants, as prepared by the plants' managers. The amounts included on Exhibit 2 include the monthly quality control and supervision costs the plant managers have budgeted for next month.

Based on your conversations with the cost accountants and plant managers and your review of your plants' production plans, you believe the budgeted amounts on Exhibit 2 are reasonable. You also believe that the relationships between these costs and spoilage costs are likely to be the same in the next month as they were last month.

Please use the budgeted costs on Exhibit 2 to ***predict monthly spoilage costs*** for next month based on what you have learned from Exhibit 1. Feel free to use a calculator.

It is important that you try to predict costs as accurately as possible. If your predictions are inaccurate, the firm's future profitability and your performance evaluations will suffer.

Recall also that your pay is based on your predictions. Your predictions will be compared to the best predictions that can be made from the data provided. The closer your predictions to the best possible predictions, the higher your pay will be.

The plant names on Exhibit 2 are disguised. It is not a good strategy to try to "match" one plant on Exhibit 2 with one or two plants on Exhibit 1. It is a ***better strategy*** to try to ***learn relationships among the costs*** and use these relationships to predict the spoilage costs.

Please complete the 20 spoilage cost predictions now.

Once you are finished with your predictions, please turn to the next page.

Advice to top management

Now that you have learned about the relationships among the various costs and have made your predictions, top management has asked you for your advice on a decision. Because of recent concerns about product quality, top management would like to ***increase its spending on quality-improvement initiatives***. However, top managers are unsure about how to make the greatest impact on quality-related costs. Thus, they are considering two different options. Note that these two options are ***mutually exclusive*** – that is, ***management will pursue only one of them, but not both***.

For help in deciding which option to pursue, management has asked you for an estimate of the effect of each of the two options. ***Your estimate should be based on the relationships you have learned from Exhibit 1.*** Please feel free to refer to Exhibit 1 when making these estimates.

Option 1: What would be the change in spoilage costs if management gave ***each plant an additional \$10,000 per month to spend on inspection***? There would be no change in any other spending levels.

Each plant's monthly spoilage costs would be expected to (circle one) **increase** or **decrease** by

about \$ _____.

Option 2: What would be the change in spoilage costs if management gave ***each plant an additional \$10,000 per month to spend on supervisors***? There would be no change in any other spending levels.

Each plant's monthly spoilage costs would be expected to (circle one) **increase** or **decrease** by

about \$ _____.

Thank you very much. Now, please ***return this packet*** to the researcher, and ***pick up your second packet***.

Exhibit 1: Plants' cost data from cost accounting system

Plant	Quality Control cost pool				Supervisory Costs cost pool			
	Inspection	Details		Pool Total	Supervisors	Details		Pool Total
		Testing	Spoilage			Training		
1	\$ 39,000	\$ 14,000	\$ 67,300	\$ 120,300	\$ 16,800	\$ 32,000	\$ 48,800	
2	46,500	18,300	54,900	119,700	28,000	23,000	51,000	
3	29,000	18,400	18,800	66,200	62,900	27,200	90,100	
4	28,000	16,200	58,300	102,500	36,400	31,300	67,700	
5	32,000	18,000	58,500	108,500	35,000	27,500	62,500	
6	59,500	12,500	19,300	91,300	58,500	26,000	84,500	
7	32,500	10,200	40,500	83,200	51,700	27,500	79,200	
8	16,900	19,000	53,200	89,100	48,500	23,100	71,600	
9	55,100	17,000	38,600	110,700	29,000	24,400	53,400	
10	36,000	19,600	32,300	87,900	49,000	28,100	77,100	
11	37,000	15,000	64,600	116,600	30,000	21,500	51,500	
12	37,300	15,900	66,400	119,600	21,600	30,600	52,200	
13	36,800	13,800	35,700	86,300	42,000	23,700	65,700	
14	50,000	18,600	26,600	95,200	56,800	24,500	81,300	
15	25,300	14,200	50,500	90,000	38,500	32,500	71,000	
16	53,600	13,000	10,700	77,300	64,300	29,100	93,400	
17	48,500	15,300	53,900	117,700	43,700	29,000	72,700	
18	37,500	10,200	64,700	112,400	22,500	25,600	48,100	
19	23,600	14,100	67,100	104,800	20,100	25,700	45,800	
20	45,500	16,200	67,300	129,000	16,600	24,900	41,500	

Exhibit 2: Plants' partial budgeted cost data

Plant	Quality Control cost pool			Supervisory Costs cost pool		
	Details			Details		
	Inspection	Testing	Spoilage	Supervisors	Training	
A	\$ 55,500	\$ 14,000		\$ 57,500	\$ 26,000	
B	23,500	16,300		35,000	32,300	
C	34,200	14,200		20,500	22,300	
D	35,000	13,000		30,000	27,900	
E	47,500	14,800		20,500	24,800	
F	39,900	15,000		40,000	30,100	
G	22,000	13,200		17,500	30,500	
H	21,500	14,500		53,000	34,200	
I	37,400	17,500		22,000	27,100	
J	33,500	11,100		30,900	27,500	
K	20,700	17,900		40,000	23,800	
L	19,000	16,800		26,900	30,200	
M	59,400	13,900		46,100	31,400	
N	18,900	10,200		45,200	29,000	
O	64,100	11,000		36,000	29,000	
P	49,000	16,800		29,600	31,300	
Q	42,500	15,000		24,200	33,700	
R	33,000	13,100		41,800	20,000	
S	58,000	16,100		64,900	21,700	
T	23,000	14,800		56,700	31,100	

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	Inspection	Details		Pool Total	Supervisors	Details		Pool Total
		Testing	Spoilage			Training		
1	\$ 16,800	\$ 14,000	\$ 67,300	\$ 98,100	\$ 39,000	\$ 32,000	\$ 71,000	
2	28,000	18,300	54,900	101,200	46,500	23,000	69,500	
3	62,900	18,400	18,800	100,100	29,000	27,200	56,200	
4	36,400	16,200	58,300	110,900	28,000	31,300	59,300	
5	35,000	18,000	58,500	111,500	32,000	27,500	59,500	
6	58,500	12,500	19,300	90,300	59,500	26,000	85,500	
7	51,700	10,200	40,500	102,400	32,500	27,500	60,000	
8	48,500	19,000	53,200	120,700	16,900	23,100	40,000	
9	29,000	17,000	38,600	84,600	55,100	24,400	79,500	
10	49,000	19,600	32,300	100,900	36,000	28,100	64,100	
11	30,000	15,000	64,600	109,600	37,000	21,500	58,500	
12	21,600	15,900	66,400	103,900	37,300	30,600	67,900	
13	42,000	13,800	35,700	91,500	36,800	23,700	60,500	
14	56,800	18,600	26,600	102,000	50,000	24,500	74,500	
15	38,500	14,200	50,500	103,200	25,300	32,500	57,800	
16	64,300	13,000	10,700	88,000	53,600	29,100	82,700	
17	43,700	15,300	53,900	112,900	48,500	29,000	77,500	
18	22,500	10,200	64,700	97,400	37,500	25,600	63,100	
19	20,100	14,100	67,100	101,300	23,600	25,700	49,300	
20	16,600	16,200	67,300	100,100	45,500	24,900	70,400	

Exhibit 2: Plants' partial budgeted cost data

Plant	Quality Control cost pool			Supervisory Costs cost pool		
	Inspection	Details		Supervisors	Training	
		Testing	Spoilage			
A	\$ 57,500	\$ 14,000		\$ 55,500	\$ 26,000	
B	35,000	16,300		23,500	32,300	
C	20,500	14,200		34,200	22,300	
D	30,000	13,000		35,000	27,900	
E	20,500	14,800		47,500	24,800	
F	40,000	15,000		39,900	30,100	
G	17,500	13,200		22,000	30,500	
H	53,000	14,500		21,500	34,200	
I	22,000	17,500		37,400	27,100	
J	30,900	11,100		33,500	27,500	
K	40,000	17,900		20,700	23,800	
L	26,900	16,800		19,000	30,200	
M	46,100	13,900		59,400	31,400	
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R	41,800	13,100		33,000	20,000	
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