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Cost Hierarchy: Evidence and Implications

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Cost Hierarchy: Evidence and Implications

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Abstract- Empirical evidence on the association between overhead costs and non-volume related cost drivers is mixed. Anderson and Sedatole (2013) offer possible explanations for the lack of evidence and find that the cost hierarchy is descriptive of the association between resource consumption and production activity. In this paper, we provide evidence on the presence of the cost hierarchy by studying the behavior of indirect production labor costs using daily data for five years from seven production departments of an industrial equipment manufacturer. We find that in addition to direct labor costs, the number of setups and number of distinct parts are also significantly associated with indirect production costs in at least six out of the seven production departments. Interestingly, despite our evidence for the existence of the cost hierarchy, the simple method of estimating these indirect costs as a proportion of only direct labor costs performs remarkably well in predicting costs.

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I. Introduction

Cost accounting textbooks and extant studies claim that indirect manufacturing costs vary not just with volume-related cost drivers such as direct labor cost, but also with batch and product-related cost drivers (e.g. Lanen et al., 2013). However, the collective empirical evidence to date on the association between overhead costs and non-volume related cost drivers is mixed (Labro, 2004; Anderson and Sedatole, 2013). If non-volume related activities are a key driver of indirect production costs, then managerial decisions based on the traditional product cost information are believed to be suboptimal, as the measured product costs are likely to be distorted (Hilton and Platt, 2014). In this paper, we provide detailed evidence on the presence of the cost hierarchy by studying the behavior of daily indirect production labor costs in multiple departments of an industrial equipment manufacturer.

Anderson and Sedatole (2013) summarize reasons provided in the literature for the failure to detect the association between indirect costs and non-volume related cost drivers. The first reason is due to the innovations in manufacturing that create a correlation between volume-related and non-volume related activities. These innovations restore the relevance of traditional volume- based cost allocation (Ittner and MacDuffie, 1995; Ittner et al., 1997: Abernethy et al. 2001). The second set of reasons pertain to the limitations of accounting data (Balakrishnan et al.,2004; Cooper and Kaplan, 1992), measurement error in proxies for activities (Foster and Gupta, 1990; Kaplan and Anderson 2004, 2007), and the timing differences between production activities (with shorter, perhaps, daily variations) and typical accounting data collection (with monthly or quarterly variations).

Many prior empirical papers that fail to detect the association between non-volume related activities have relied on cross-sectional data (Foster and Gupta, 1990; Noreen and Soderstrom, 1994; Ittner and MacDuffie, 1995; Ittner et al., 1997). Time-series analysis can address many of the limitations of cross-sectional studies. Our study, similar to Anderson and Sedatole (2013), utilizes daily production and cost data pertaining to direct and indirect labor over a period of five years from seven production departments in two manufacturing plants operated by a Fortune 500 company. Indirect production labor activities comprise materials handling, machine setup and team meetings undertaken within individual production departments and exclude common support activities provided by a separate organizational unit such as engineering and maintenance. The short cycle times (0.05 to 0.14 day, on average) in the production departments at our research site imply a tight matching between indirect labor costs incurred each day in production departments and the daily activity measures that drive these costs. This tight association between daily indirect production labor costs and production activity presents an excellent opportunity to examine the time-series behavior of these variables using daily data.

We provide evidence on the positive association between indirect costs and batch and product-level activities at the daily level, as predicted by the cost hierarchy. We also document that aggregation of data at weekly and monthly level reduces the association between indirect costs and batch and product-level activities. Our research site represents a common manufacturing environment involving multiple production departments ranging from fabrication to assembly, enhancing the external validity of our analysis. In addition, data identified with individual production departments allow us to better match costs with activities and examine patterns in these relations that vary across different production departments with different process characteristics.

Few, if any, studies have explicitly investigated how different production processes moderate cost driver effects (Ittner and Larcker, 2001). Although not

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highlighted as a part of the main results, we also examine whether indirect costs vary in proportion to activities (Noreen and Soderstrom, 1994) and provide evidence rejecting the proportionality assumption.

In addition to providing empirical evidence on cost hierarchy, we measure the extent of product cost distortions induced by traditional labor-based cost allocations. This analysis provides further evidence on the usefulness of activity based costing systems for managerial decision making (Banker et al., 1990) as it documents that the product cost estimates based on the traditional system may be distorted. However, we do not find that a more detailed cost system based on our cost hierarchy results in substantially better cost prediction. Rather we document that traditional costing system performs as well as a cost system based on non-volume related cost drivers for the prediction/planning of total costs at our research site. This last result cautions that the overall impact of sophisticated costing systems on managerial decision making and firm performance may be limited, and echoes the skepticism of Dopuch (1993) and results of Ittner et al. (2002).

The remainder of this paper is organized as follows. Section 2 describes the research site, and presents descriptive statistics for the data collected at the research site. The estimation models and empirical results are discussed in section 3. Some managerial implication are presented in section 4. Concluding remarks are offered in section 5.

II. Research Site and Data

a) *Research Site*

To conduct a time-series analysis of indirect production labor costs we looked for a research site that could provide us with detailed and reliable data on the variables of interest for a sufficiently long time period. To enhance the external validity of our analysis, we required a site that represented a common manufacturing environment involving multiple production departments ranging from fabrication to assembly. We wanted data identified with individual production departments to allow us to better match costs with activities, and examine patterns in these relations that varied across different production departments with different process characteristics. The research also required detailed data on indirect and direct labor costs and other potential cost drivers. The research site we selected satisfied all of these criteria.

We collected the data for this research from a large manufacturer of floor maintenance equipment such as scrubbers, sweepers, burnishers and other cleaning equipment. The company is a world leader in its industry segment, and has received numerous awards for its manufacturing and employment practices. We obtained daily data for a consecutive five year period from the two plants of the company which are in close proximity to each other. A flow chart of the production process is presented in Figure 1. The production process begins in plant A, where parts and components such as casings, frames, and brushes are manufactured in accordance with production orders. These components are then shipped to plant B for further processing and assembly. The departments in Plant A exhibit a job shop type production environment with many small batches and workers performing a larger proportion of indirect activities, while the departments in Plant B exhibit an assembly line type production environment with fewer and larger batches and workers performing a smaller proportion of indirect activities.

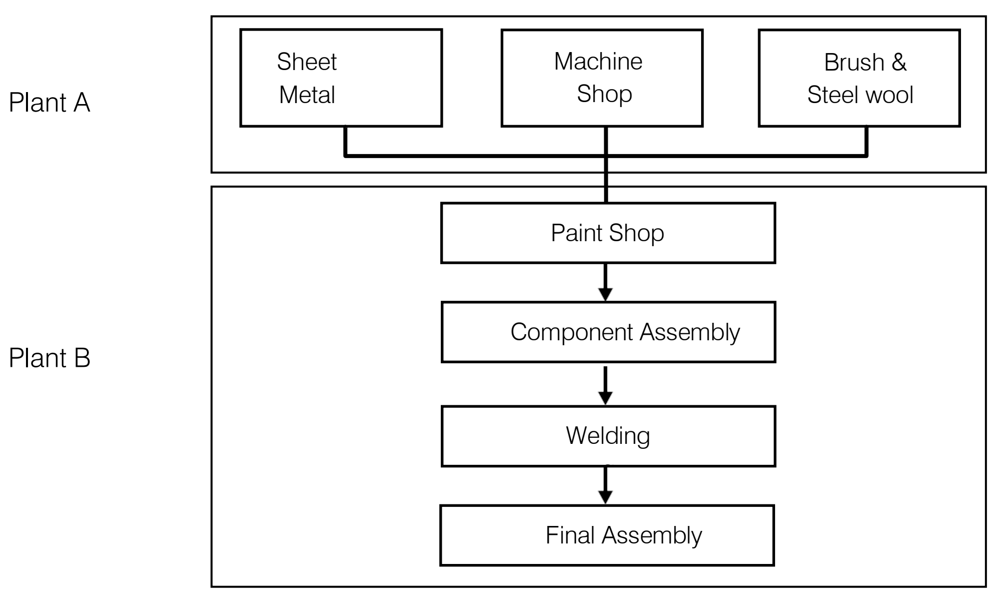

Figure 1: Production Process Flow Chart

Plant A has three production departments: Sheet Metal, Machine Shop, and Brush & Steel Wool. The Sheet Metal department produces the casings and other components made of steel plates. The Machine Shop produces a variety of machine related parts such as engine mountings, frames, brackets, bearings and rods. The Brush & Steel Wool department manufactures different types of brushes that perform the cleaning function in the assembled equipment. The production processes in these three departments are operated in parallel, and there is no sequential dependence among them.

Plant B has four production departments: Paint Shop, Component Assembly, Welding, and Final Assembly. The parts are painted in the Paint Shop and then assembled into components in the component assembly department. These assembled components are welded together in accordance with the product design in welding department. The welded components are finally assembled into the finished product ready for shipment to customers.

Each production department represents a different production activity and a different pattern of consumption of activity resources. Both direct and indirect labor costs are incurred in all seven production departments. Direct labor hours are associated with productive operations for the manufacture or assembly of parts or components. Indirect labor hours are associated with other activities such as materials handling, machine setup, team meetings and inspection. The cost accounting system at our research site allocates indirect costs to individual products on the basis of direct labor costs. A separate overhead rate is determined for the allocation of each production department's indirect costs.

We interviewed managers and staff from production and cost accounting departments at our research site to assess production processes, products, and existing cost records and procedures. There were no major changes in products or manufacturing operations during the five year period covered by our study. We also obtained sample reports for production planning, cost allocations, daily departmental labor activity and expense summary. We collected production and labor cost data electronically with the assistance of the plants' information systems personnel. The data set includes the daily activities of all production department workers. The time spent on different activities is classified into direct and indirect labor. Direct labor hours are further identified with a part number, work center where the part was produced, customer order number and quantity, standard labor hours, and quantity produced.

The data we obtained are an integral part of the company's information system for production labor accounting. These data are entered directly into the company's computerized system daily by production workers in the presence of their supervisors. The data are maintained by the central information systems department of the company and constitute the source information for periodic reports for payroll, accounting and manufacturing department managers. Payroll staff use these data to process labor wage payments. Accounting staff use these data for cost allocation, inventory valuation, standard costing and variance analysis. Manufacturing staff use these data for production planning purposes and for updating manufacturing standards. Because of the importance of these data, several internal checks exist to ensure the integrity and reliability of the data. We cross-checked the data with summary reports obtained from senior managers. We also plotted the data to visually scan for outliers or otherwise unusual data records. We determined that these data are a reliable record of the daily work in the plants' production departments.

b) Variable Construction

We measure the daily indirect production labor cost (ILCOST) separately for each of the seven production departments. The detailed daily data also allow us to construct cost drivers based on the cost hierarchy framework of unit-related, batch-related, product-sustaining and facility- sustaining activities described by Cooper and Kaplan (1991). The demand for unit-related activity resources varies directly with the number of units produced. Examples include direct labor and direct materials. We selected direct labor dollars (DLCOST) as the unit-level cost driver in our analysis because the present cost accounting system at our research site allocates indirect costs based on this measure[1].

Batch-related activities occur each time a batch is processed or at the beginning or end of each production run. These activities include machine setup, material movement and material requisition. We chose the number of setups (NUMSETUPS) as a batch-level activity cost driver (Cooper and Kaplan, 1987; Anderson and Sedatole, 2013). Setup activities differ across departments. For example, in the Machine Shop, a setup involves only changing and correctly positioning the tools in the machines. Setups in the Paint Shop are longer because machines require a thorough cleanup before colors are changed. Setups are also lengthy in the Final Assembly department because they involve coordination and movement of many sub-assemblies.

Product-sustaining activities are required to handle the additional complexity resulting from an increase in the number of products or parts. Examples of product sustaining activities include engineering change orders, process engineering, maintaining bill of materials, and preparing routing sheets. Within a

[1] DLCOST is highly correlated to direct labor hours (DLHOURS), and the results reported here do not change appreciably when this alternative unit-level cost driver is employed in our analysis.

production department, product-sustaining activities are performed to deal with the increased need for coordination on the shop floor and among production team members when more distinct parts are manufactured. In keeping with prior studies (Cooper and Kaplan 1991, Banker et al. 1995, Banker et al. 1990)[2], we included the number of distinct parts (NUMPARTS) produced in a production department on each day as a product-sustaining cost driver in our analysis. The number of distinct parts produced in a day reflects the demand for additional activities such as increased coordination, material movements, and storage that are not captured by number of setups. In the Machine Shop, distinct parts produced are the different types of mountings, frames and brackets. In the Paint Shop and Welding departments, distinct parts produced are the different painted and welded components. In the Final Assembly department, the parts represent the assembled products sold to the customers.

Our data set enabled us to construct the following daily variables by production department to examine the behavior of indirect production labor costs: number of workers (NUMWORKER), number of setups performed (NUMSETUPS), number of distinct parts manufactured (NUMPARTS), direct labor hours (DLHOURS), direct labor cost (DLCOST), indirect labor hours (ILHOURS), and indirect labor cost (ILCOST). Table 1 presents descriptive statistics for these variables for each of the seven production departments.

Table 1: Descriptive Statistics (Daily Data) (Standard deviations are in parentheses)

Variable (Per day)	Sheet Metal (n=1365)	Machine Shop (n=1423)	Brush & Steel Wool (n=1314)	Paint Shop (n = 1302)	Component Assembly (n=1368)	Welding (n =1327)	Final Assembly (n = 1391)
Number of Workers (**NUMWORKER**)	26.38 (5.87)	30.97 (9.16)	15.09 (3.28)	16.80 (3.06)	30.12 (7.24)	32.60 (5.84)	32.86 (9.13)
Number of Distinct Parts (**NUMPARTS**)	136.71 (39.22)	58.34 (18.34)	13.96 (4.20)	55.99 (23.50)	30.96 (10.67)	59.44 (13.70)	21.06 (5.72)
Number of Setups (**NUMSETUPS**)	191.72 (62.76)	54.45 (21.75)	15.89 (8.48)	11.85 (4.770	20.31 (10.34)	53.41 (17.48)	7.37 (7.09)
Number of Direct Labor Hours (**DLHRS**)	126.99 (36.24)	184.19 (64.89)	87.64 (27.20)	97.57 (32.33)	188.24 (57.27)	217.40 (57.75)	226.73 (77.13)
Number of Indirect Labor Hours (**ILHRS**)	73.52 (24.13)	58.10 (27.35)	23.19 (14.49)	26.91 (12.54)	34.79 (19.53)	45.92 (16.83)	24.49 (20.90)
Indirect Labor Cost (**ILCOST**) as a % of Direct Labor Cost (**DLCOST**)	58.24 (13.53)	34.11 (117.31)	28.76 (36.34)	30.19 (50.25)	21.23 (79.84)	21.79 (12.36)	13.10 (67.04)

A comparison across the seven production departments reflects different patterns of consumption of the activity resources. The averages for the number of workers, the number of distinct parts produced and the number of setups required are very different across departments, reflecting the differences in the requirements of the production process at each stage. Overall, there are systematic differences between the departments in Plant A and those in Plant B that reflect the job shop type environment in the former and the assembly line type setting in the latter. The departments in Plant A have more setups and a higher proportion of indirect labor to direct labor than the departments in Plant B. In particular, the Sheet Metal department has considerably more distinct parts and setups than the other six departments. It also has more setups than parts as some of the parts require more than one setup for certain operations. The Brush & Steel Wool and Paint Shop departments are small, employing relatively few workers and requiring few setups. The number of distinct parts manufactured daily is high relative to the number of setups in the Paint Shop reflecting the flexible automation in that department.

[2] Facility-sustaining activities relate to plant management and facilities maintenance. We do not include any measure to reflect these activities because labor assigned to production departments is not responsible for any facility- sustaining activities

In Final Assembly, the number of distinct parts is small, reflecting only the number of products, rather than all the parts and components. The number of setups is low indicating the long production runs in that department. The department also has the fewest number of workers and the lowest proportion of indirect to direct labor reflecting the high level of labor intensity of its production process. For each department the standard deviations and distribution deciles (not shown here) of all variables reveal considerable variation in the daily data within each year. Their distributions exhibit little skewness, with the median values (not shown here) very close to the means.

Table 2 reports, by department, Pearson correlations between ILCOST, DLCOST, NUMSETUPS and NUMPARTS in the upper triangles and Spearman correlations in the lower triangles. Except where noted, all of the correlations are significant at the 1% level suggesting that omitting cost drivers may result in biased coefficients. ILCOST is significantly correlated with each of the other three variables. The magnitude of the Pearson correlation of ILCOST with DLCOST is the lowest for the three departments in Plant A, but the highest in three of the four departments in Plant B, reflecting once again the differences in the job shop versus assembly line type settings in the two plants. Because different parts usually require separate setups, NUMPARTS and NUMSETUPS are highly correlated in all departments except the Paint Shop and the Final Assembly departments. The magnitudes of all correlation coefficients differ considerably across departments and plants, reflecting differences in process characteristics. Pearson correlation coefficients range between 0.65 and 0.93 in the Sheet Metal and Machine Shop departments, and between 0.48 and 0.60 in the Brush & Steel Wool department. All except two of the coefficients range from only 0.02 to 0.43 for three of the four departments in Plant B, but they are between 0.50 and 0.84 in the Welding department.

Table 2: Panel a Pearson and Spearman Correlations for Production Departments in Plant A (Daily Data)

Sheet Metal

Variable	ILCOST	DLCOST	NUMSETUPS	NUMPARTS
ILCOST	1.00	0.65	0.68	0.68
DLCOST	0.59	1.00	0.73	0.78
NUMSETUPS	0.68	0.56	1.00	0.93
NUMPARTS	0.63	0.62	0.93	1.00

Machine Shop

Variable	ILCOST	DLCOST	NUMSETUPS	NUMPARTS
ILCOST	1.00	0.76	0.88	0.83
DLCOST	0.57	1.00	0.82	0.78
NUMSETUPS	0.80	0.68	1.00	0.93
NUMPARTS	0.76	0.68	0.94	1.00

Brush & Steel Wool

Variable	ILCOST	DLCOST	NUMSETUPS	NUMPARTS
ILCOST	1.00	0.48	0.54	0.56
DLCOST	0.53	1.00	0.55	0.60
NUMSETUPS	0.57	0.50	1.00	0.70
NUMPARTS	0.58	0.56	0.71	1.00

Please see Table 1 for the definition of variables. Pearson correlations are above the diagonal, Spearman correlations are below the diagonal. All correlations are significant at the 1% level.

Table 2: Panel B Pearson and Spearman Correlations for Production Departments in Plant B (Daily Data)

Paint Shop

Variable	ILCOST	DLCOST	NUMSETUPS	NUMPARTS
ILCOST	1.00	0.37	0.20	0.25
DLCOST	0.34	1.00	0.41	0.43
NUMSETUPS	0.21	0.35	1.00	0.30
NUMPARTS	0.27	0.38	0.29	1.00

Global Journal of Management and Business Research (D) Volume XXI Issue II Version I Year 2021

Component Assembly

Variable	ILCOST	DLCOST	NUMSETUPS	NUMPARTS
ILCOST	1.00	0.34	0.36	0.34
DLCOST	0.28	1.00	0.37	0.43
NUMSETUPS	0.41	0.19	1.00	0.80
NUMPARTS	0.35	0.14	0.77	1.00

Welding

Variable	ILCOST	DLCOST	NUMSETUPS	NUMPARTS
ILCOST	1.00	0.50	0.50	0.51
DLCOST	0.45	1.00	0.67	0.71
NUMSETUPS	0.50	0.51	1.00	0.84
NUMPARTS	0.47	0.56	0.83	1.00

Final Assembly

Variable	ILCOST	DLCOST	NUMSETUPS	NUMPARTS
ILCOST	1.00	0.31	0.09	0.26
DLCOST	0.38	1.00	0.02@	0.60
NUMSETUPS	0.26	0.06*	1.00	0.30
NUMPARTS	0.34	0.48	0.35	1.00

Please see Table 1 for the definition of variables. Pearson correlations are above the diagonal, Spearman correlations are below the diagonal. @ indicates not significant at conventional levels. * indicates significant at 5% level. All other correlations are significant at the 1% level.

III. Estimation Models and Results

Following prior studies, we estimate two cost models. The first one to reflect the existing labor-based cost accounting system at our research site that allocates indirect production labor costs to individual jobs based on direct labor costs separately for each production department and is based on the assumption that for each production department, direct labor cost is the only cost driver. We estimate the second cost model to test the presence of the cost hierarchy. Production managers at our research site indicated that indirect production labor hours arise because of activities such as machine setup, materials movement, and inspection. Therefore, we estimate a multiple regression model of indirect production labor costs and three cost drivers: direct labor costs (unit-related driver), number of setups (batch-related driver) and number of parts (product-sustaining driver) identified for this study.

Model 1: $ILCOSTt = \beta 0 + \beta 1\ DLCOSTt + \varepsilon t$

Model 2: $ILCOSTt = \gamma 0 + \gamma 1\ DLCOSTt + \gamma 2\ NUMSETUPSt + \gamma 3\ NUMPARTSt + \varepsilon t$

The hypothesis that indirect production labor costs are related to cost drivers other than production volume is verified by conducting a joint test of whether the coefficients of both NUMSETUPS and NUMPARTS are zero. Based on our discussion of the production process characteristics, we expect systematic differences in the estimated coefficients of model 2 between the departments in the two plants. For the job shop type production departments in Plant A, we expect the coefficient γ2 (for setups) to be greater and the coefficient γ3 (for number of parts) to be smaller than the corresponding estimated coefficients for the assembly line type production departments in Plant B.[3]

[3] Implicit in this allocation procedure is the assumption that indirect production labor costs vary proportionally with the unit-related measure, direct labor costs (Noreen and Soderstrom 1994). Although our main research questions do not pertain to the issue of whether costs are proportional to the underlying activity (Noreen and Soderstrom, 1994), a straightforward test of proportionality involves estimating the above linear regression model using time-series observations and then testing whether the intercept is zero ($\beta 0=0$). The proportionality assumption in Model 2 is evaluated as before by testing whether $\gamma 0 = 0$. Although not discussed in the results section but shown in Table 3, the proportionality assumption ($\beta 0 = 0$) is rejected at the 1% significance level for all seven departments. In each case, the estimated β0 coefficient is positive, suggesting increasing returns to scale for indirect activities. The estimated γ0 coefficient in Model 2 (shown in Table 4) is positive for all seven departments, but significant only for four suggesting violation of proportionality assumption and presence of increasing returns to scale for these departments.
Tests based on the Box-Cox (1964) transformation (Greene 2011) reject the linear specification, but not the loglinear specification, of

For each of the seven production departments, we estimated a separate regression, for the two models specified above. To ensure that inferences from the estimated models are reasonable, we examined the assumptions underlying OLS regression and checked for potential data problems. First order serial correlation was 0.46 for the Brush & Steel Wool department and ranged between 0.16 and 0.27 for the other six departments for both models. Durbin-Watson statistics indicated that first order serial correlations were significant in all cases. All of the estimation results reported in this paper are after correcting for serial correlation using the Park-Mitchell (1980) variant of the Prais-Winsten (1954) method.

We checked the OLS residuals for consistency with the assumption that they are distributed normally. No deviations from normality were indicated at conventional levels of significance using the Kolmogorov test statistic. After the logarithmic transformation of dependent and independent variables, Glesjer's (1969) test did not reject homoskedasticity, but White's (1980) general test for misspecification indicated the presence of heteroskedasticity for all seven departments for model 2, and for three cases for model 1. Therefore, in Table 4 we report results based on White's heteroskedasticity consistent standard errors, but in Table 3, we report standard t- and F-statistics. None of the test results based on White's corrected statistics are different from the corresponding results based on Standard t- and F-statistics for model 1, but for model 2 White's corrected statistic does not reject the null hypothesis that $\gamma 3=0$ in Machine Shop and Component Assembly. We also checked for contemporaneous correlations between the residuals for different departments, found no significant contemporaneous correlations and, therefore, concluded that there was no need for estimating our models as a system of seemingly unrelated regressions.

both models for all seven departments. The rejection of the linear model with DLCOST as the only cost driver can also be interpreted as further evidence against proportionality. Test of proportionality with the loglinear version of model 1 corresponds to the test of the null hypothesis: $\beta 1 = 1$ because proportionality, (i.e. ILCOST = w*DLCOST) implies, $ln(\text{ILCOST}) = ln\ w + 1{*}ln(\text{DLCOST})$. The results (not shown) indicate that proportionality is rejected for five departments. Tests of proportionality with the loglinear version of model 2 correspond to the test of constant returns to scale hypothesis: $\gamma 1 + \gamma 2 + \gamma 3 = 1$. This null hypothesis is rejected for five departments (results not shown). We also estimated both models 1 and 2 separately for each of the five years covered by our data set for each of the seven departments. Proportionality (results not shown) is rejected in 28 out of 35 regressions. Estimation results (not shown) based on weekly data rejected proportionality in all seven departments. Estimation of model 1 based on monthly data (Table 5) indicated that proportionality is rejected for four of the seven departments. In the multiple drivers model 2 based on monthly data (Table 6), $\gamma 0$ is significant in only one department.

Finally, even in ARMA models (Table 7), the proportionality hypothesis is rejected for five out of the seven departments. However, the magnitudes of $\beta 1$ range between 1.00 and 1.05 in four of the seven departments. This suggests a need to evaluate the economic significance of the deviation from proportionality. In summary, all different specifications of our models reject proportionality of costs.

Global Journal of Management and Business Research (D) Volume XXI Issue II Version I Year 2021

Table 3: Tests of a Labor Based Cost Model (Daily Data) (t-statistics in parentheses)

Model 1: $ILCOST_t = \beta_0 + \beta_1 DLCOST_t$

Variable	Sheet Metal (n=1365)	Machine Shop (n=1423)	Brush & Steel Wool (n=1314)	Paint Shop (n=1302)	Component Assembly (n=1368)	Welding (n=1327)	Final Assembly (n=1391)
Intercept t-stat ($\beta 0=0$)	93.80 (6.44)**	84.83 (5.14)**	45.67 (5.74)**	131.84 (13.26)**	126.20 (7.23)**	152.68 (8.54)**	78.80 (4.30)**
DLCOST t-stat ($\beta 1=0$)	0.50 (45.28)**	0.27 (32.24)**	0.20 (16.79)**	0.14 (14.66)**	0.12 (13.81)**	0.14 (20.83)**	0.08 (8.86)**
Adj. R^2	0.60	0.42	0.18	0.14	0.12	0.25	0.08
Durbin-Watson statistic Before Prais-Winsten Correction After Prais-Winsten Correction	1.48** 2.04	1.45** 1.99	1.07** 2.14	1.62** 2.00	1.61** 2.02	1.71* 2.01	1.66** 2.05

ILCOST = Indirect Labor Cost
DLCOST = Direct Labor Cost
NUMSETUPS = Number of Setups
NUMPARTS = Number of Distinct Parts

** indicates significant at the 5% level.*
*** indicates significant at the 1% level.*

Estimation results for model 1 are presented in Table 3. The adjusted R2 varies across regressions, ranging from 0.08 to 0.60. Estimation results for the multiple regressions relating overhead costs to unit, batch and product level cost drivers are presented in Table 4. The adjusted R2 are higher for model 2 than for model 1, ranging from 0.09 to 0.78.[4] Results in Table 4 also indicate that all three cost drivers are associated significantly and positively with indirect production labor costs, except for the Paint Shop department regression in which NUMSETUPS is not significant and for the Machine Shop and Component Assembly department regressions where NUMPARTS is significant only at the 12% level. The joint test of $\gamma 2=\gamma 3=0$ is rejected at the 1% level for all seven departments, indicating that indirect production labor costs are associated with cost drivers other than direct labor costs alone. With the exception of Brush & Steel Wool department, the coefficients of NUMSETUPS are generally greater and those for NUMPARTS are generally smaller for the Plant A departments than the corresponding coefficients for the Plant B departments.

[4] A drop in the estimated $\gamma 0$ is expected as the portion of the setup and parts impact not captured by the volume variable (DLCOST) becomes imbedded in the intercept in model 1.

Table 4: Parameter Estimates Relating Overhead Costs to Multiple Cost Drivers (Daily Data) (White's adjusted statistics in parentheses)

Model 2: $ILCOST_t = \gamma_0 + \gamma_1 DLCOST_t + \gamma_2 NUMSETUPS_t + \gamma_3 NUMPARTS_t$

Variable	Sheet Metal (n=1365)	Machine Shop (n=1423)	Brush & Steel Wool (n=1314)	Paint Shop (n=1302)	Component Assembly (n=1368)	Welding (n=1327)	Final Assembly (n=1391)
Intercept	47.06 (22.22)**	22.75 (0.58)	12.28 (1.54)	114.28 (48.91)**	86.64 (6.00)**	72.42 (7.54)**	24.84 (0.34)
DLCOST	0.09 (34.52)**	0.11 (55.85)**	0.05 (9.26)**	0.11 (95.69)**	0.08 (33.29)**	0.07 (62.96)**	0.06 (33.53)**
NUMSETUPS	3.40 (222.64)**	6.99 (31.49)**	6.66 (108.43)**	1.10 (1.38)	5.41 (32.70)**	2.33 (29.76)**	2.62 (9.75)**
NUMPARTS	0.78 (4.90)*	1.66 (1.01)	8.07 (26.10)**	0.67 (13.98)**	1.38 (1.55)	3.02 (27.72)**	4.73 (7.39)**
Adj. R^2	0.78	0.51	0.33	0.15	0.18	0.30	0.09
P(Model) P(Multiple Drivers: $\gamma 2=\gamma 3=0$)	0.0001 0.0001	0.0001 0.0001	0.0001 0.0001	0.0001 0.0001	0.0001 0.0001	0.0001 0.0001	0.0001 0.0001
Durbin-Watson Statistic Before Prais-Winsten Correction After Prais-Winsten Correction	1.67* 2.01	1.43** 1.98	1.07** 2.11	1.62* 2.01	1.64** 2.02	1.69* 2.01	1.65* 2.04

ILCOST = Indirect Labor Cost
DLCOST = Direct Labor Cost
NUMSETUPS = Number of Setups
NUMPARTS = Number of Distinct Parts

** indicates significant at the 5% level.*
*** indicates significant at the 1% level.*

a) Sensitivity Analysis

Models 1 and 2 are misspecified if their maintained assumption of linearity (albeit, weaker than the testable assumption of proportionality) is not valid. In addition, as in Noreen and Soderstrom (1994), our linear models are likely to have heteroskedastic residuals. Furthermore, tests based on the Box-Cox (1964) transformation (Greene 2011) reject the linear specification, but not the loglinear specification, of both models for all seven departments. Therefore, in keeping with Noreen and Soderstrom (1994) and Banker et al. (1995), we also estimated loglinear model after logarithmic transformation of the variables.[5] Consistent with the linear model (results not shown here), NUMSETUPS is significant for six and NUMPARTS for all seven departments.

We employed Belsley, Kuh and Welsch (1980) collinearity diagnostics to examine multicollinearity between independent variables. Both the condition index and VARPROP are above the cutoffs suggested by Belsley, Kuh and Welsch (1980) for all seven regressions, indicating a very high degree of multicollinearity. As a result, coefficient estimates are sensitive to small model changes, although they are unbiased. Since collinearity is a data problem, we examined the robustness of our results with different subsets of sample data. We re-estimated both models separately for each of the five years covered by our data set for each of the seven departments. DLCOST has a significant and positive coefficient in 27, NUMSETUPS in 28, and NUMPARTS in 20 out of the 35 estimated regressions. The joint test of $\gamma 2=\gamma 3=0$ is rejected in only 3 of the 35 regressions. These results provide additional support for the significance of multiple cost drivers.

We also examined the impact of extreme and influential observations using the criteria outlined in Belsley, Kuh and Welsch (1980). We computed the RSTUDENT, COV, DFFITS and h metrics. We classified observations as influential if two or more of the computed metrics exceeded the cutoff values suggested by Belsley, Kuh and Welsch (1980), deleted them from the sample and re-estimated both models for all departments. This procedure did not lead to any appreciable change in the results.

b) Aggregating Costs and Activities on a Monthly Basis

Because our focus is on indirect labor costs within each production department, and because production cycle times in all departments are

[5] We also estimated two other models: one linear and the other loglinear, with labor hours instead of costs as the two variables. The results (not shown here) remain qualitatively the same

considerably shorter than a day, there is tight matching of indirect costs with their cost driver levels each day. Therefore, our analysis at the daily level provides the most powerful tests. However, to further assess the robustness of our results, we also aggregated the data at the weekly and monthly levels and re-estimated the models. Anderson and Sedotale (2013) had found that, at their research site, monthly aggregation obscured the link between resource consumption and batch-related activities. Estimation results based on weekly data (not shown here) indicate that DLCOST is significant in all except the Brush & Steel Wool and Welding departments. NUMSETUPS is significant in all the departments of Plant A and two departments in Plant B. However, NUMPARTS is significant in only three departments of Plant B.

Estimation results based on monthly level data are displayed in Tables 5 and 6. DLCOST is significant in all except the Brush & Steel Wool department. NUMSETUPS is significant in all the three departments of Plant A but none of the four departments in Plant B, consistent with our expectations that setups are more important in job shop type settings. NUMPARTS is significant in only the Welding department. However, the hypothesis that the coefficients of both NUMSETUPS and NUMPARTS are zero is rejected for all except the Paint Shop and Final Assembly departments. We surmise that this results from the severe multicollinearity between NUMPARTS and NUMSETUPS. Re-estimating the regression after deleting either of these two variables yields a positive and significant coefficient for the other variable for all seven departments. Thus, with aggregated monthly data, direct labor and either one of NUMSETUPS or NUMPARTS continue to account for a large share of the variation in indirect labor costs.

Table 5: Tests of a Labor Based Cost Model (Monthly Data) (t-statistics in parentheses)

Model 1: $ILCOST_t = \beta_0 + \beta_1 DLCOST_t$

Variable	Sheet Metal (n=60)	Machine Shop (n=60)	Brush & Steel Wool (n=60)	Paint Shop (n=60)	Component Assembly (n=60)	Welding (n=60)	Final Assembly (n=60)
Intercept t-stat (β0=0)	4621.71 (3.94)**	6060.65 (4.24)**	-408.73 (-0.63)	2549.49 (4.26)**	1624.25 (1.49)	1544.75 (2.05)**	448.73 (0.37)
DLCOST t-stat (β1=0)	0.41 (10.45)**	0.21 (8.60)**	0.32 (5.90)**	0.13 (4.04)**	0.14 (5.06)**	0.17 (10.76)**	0.10 (4.91)**
Adj. R^2	0.65	0.56	0.37	0.21	0.30	0.66	0.29
Durbin-Watson Statistic Before Prais-Winsten Correction After Prais-Winsten Correction	1.42** 1.49	1.87 1.92	0.94** 1.36	1.29** 1.79	1.35** 1.78	1.35** 1.69	1.63 1.98

ILCOST = Indirect Labor Cost
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** indicates significant at the 5% level.*
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c) ARMA Models

In our earlier models we assumed that time-series effects are captured by a first-order autoregressive process. There are two problems with this assumption. First, it is possible that time- series data over a five-year exhibit non-stationarity. For instance, indirect production labor costs and the three explanatory variables may exhibit an upward trend over time because of an increase in sales over this period. Second, all of these variables may exhibit persistence because they represent committed resources that cannot be adjusted in the short-run (Cooper and Kaplan 1992) and because seasonality in demand patterns for the finished products persists over several days. Non-stationarity and persistence in time-series data increase the probability of spurious correlations between the variables in a regression (Harvey 1981, McCleary and Hay 1981).

To detect non-stationarity, we first employ the Dickey-Fuller tests for unit roots (Hamilton 1994, pp.486-501). This procedure involves estimating the model $Y_t = \alpha + \rho Y_{t-1} + u_t$ (where Y is the variable under consideration) by OLS regression using daily data and testing whether $\rho = 1$. Because the t-statistic obtained under the null hypothesis is not normally distributed, modified critical t-values (T-values) tabulated by Schmidt (1988) are used. The results of the univariate models of the dependent and independent variables indicate that the processes are stationary. Since stationarity assumptions hold, we can estimate the ARMA models without correcting for non- stationarity.

Next, we model the indirect production labor costs as an ARMA process with direct labor cost (for model 1), and direct labor costs, number of setups and number of distinct parts (for model 2), as the explanatory variables. We estimated several linear models with only autoregressive or moving average terms using the maximum likelihood method. Diagnostic tests based on the Q- statistic indicated that the resulting error terms were not consistent with the white noise assumption. Since trend and seasonal components of economic time series tend to combine multiplicatively, logarithmic transformations are usually applied to obtain an additive formulation upon which the statistical treatment is based (Harvey 1993, pp. 107). Therefore, we took logarithms of all variables, observing that seasonal patterns were more stable after the logarithmic transformation. For model 1, higher order ARMA processes without differencing resulted in errors that are not white noise. Therefore, we estimated the ARMA processes after differencing by specifying the following models:

Model 3: $ln\ \text{ILCOST}_t = \beta_0 + \beta_1 ln\ \text{DLCOST}_t + \alpha_1 ln\ \text{ILCOST}_{t-1} - \mu_1\varepsilon_{t-1} + \varepsilon_t.$

Model 4: $ln\ \text{ILCOST}_t = \gamma_0 + \gamma_1 ln\ \text{DLCOST}_t + \gamma_2 ln\ \text{NUMSETUPS}_t + \gamma_3 ln\ \text{NUMPARTS}_t + \delta_1 ln\ \text{ILCOST}_{t-1} - \mu_1\varepsilon_{t-1} + \varepsilon_t.$

Here $\alpha 1$ and $\delta 1$ are the autoregressive coefficients and $\mu 1$ is the moving average coefficient. The coefficients $\beta 1$, $\gamma 1$, $\gamma 2$ and $\gamma 3$ are interpreted as the short-term or impact effects of the independent variables on ILCOST (Greene, 2011).

We used the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) to select the best model among higher order ARMA processes. The first-order ARMA model yielded the minimum AIC and SBC values indicating that the error process was best represented by a first-order ARMA process. The resulting Q-statistics were insignificant indicating that this first-order ARMA model is the best parsimonious model.

Table 7: Tests of a Labor Based Cost Model with an ARMA (1,1) Model (Daily Data) (t-statistics in parentheses)

$$ln(\text{ILCOST}_t) = \beta_0 + \beta_1 ln(\text{DLCOST}_t) + \alpha_1 ln(\text{ILCOST}_{t-1}) - \mu_1\, \varepsilon_{t-1} + \varepsilon_t$$

Variable	Sheet Metal (n=1365)	Machine Shop (n=1423)	Brush & Steel Wool (n=1314)	Paint Shop (n=1302)	Component Assembly (n=1368)	Welding (n=1327)	Final Assembly (n=1391)
Intercept	-0.0002 (-2.14)**	-0.0002 (-0.61)	0.0006 (0.72)	-0.0001 (-0.15)	-0.0003 (-0.47)	-0.0001 (-0.43)	-0.0006 (-0.37)
εt-1 (MA parameter)	0.98 (215.56)**	0.97 (148.69)**	0.95 (106.37)**	0.96 (125.66)	0.97 (122.37)**	0.98 (175.36)**	0.93 (81.23)**
*ln*ILCOSTt-1 (AR parameter)	0.14 (5.30)**	0.19 (6.95)**	0.09 (3.04)**	0.06 (2.21)*	0.17 (5.92)**	0.10 (3.57)**	0.16 (5.24)**
ln DLCOST H0 : β1 = 0 H0 :β 1 = 1	1.03 71.57)** (1.75)*	1.32 (70.69)** (17.04)**	0.85 (21.63)** (-3.85)**	1.05 (36.04)** (1.81)*	1.12 (30.53)** (3.18)**	1.02 (43.60)** (0.82)	1.03 (13.86)** (0.46)

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** indicates significant at the 5% level.*
*** indicates significant at the 1% level.*

Table 8: Parameter Estimates Relating Overhead Costs to Multiple Cost Drivers in an ARMA (1,1) Model (Daily Data) (t-statistics in parentheses)

$$ln\ (\text{ILCOST}_t) = \gamma_0 + \gamma_1 ln(\text{DLCOST}_t) + \gamma_2 ln(\text{NUMSETUPS}_t) + \gamma_3 ln(\text{NUMPARTS}_t) + \alpha_1 ln(\text{ILCOST}_{t-1}) - \mu_1\varepsilon_{t-1} + \varepsilon_t$$

Variable	Sheet Metal (n=1365)	Machine Shop (n=1423)	Brush & Steel Wool (n=1314)	Paint Shop (n=1302)	Component Assembly (n=1368)	Welding (n=1327)	Final Assembly (n=1391)
Intercept	1.26 (14.06)**	-0.10 (-0.65)	1.40 (5.21)**	-1.43 (-6.66)**	-0.51 (-1.69)*	-0.33 (-1.69)*	-1.80 (-3.19)**
εt-1 (MA parameter)	0.84 (25.99)**	0.23 (2.19)*	--	--	0.54 (6.69)**	0.19 (1.94)*	0.69 (14.97)**
ln(ILCOSTt-1) (AR parameter)	0.94 (45.01)**	0.45 (4.63)**	0.49 (20.11)**	0.16 (5.77)**	0.72 (10.67)**	0.45 (3.16)**	0.87 (27.77)**

*ln*DLCOST	0.16 (6.58)**	0.38 (10.31)**	0.25 (5.19)**	0.91 (23.78)**	0.60 (12.62)**	0.51 (11.84)**	0.65 (7.27)**
*ln*NUMSETUPS	0.74 (16.08)**	0.57 (10.56)**	0.43 (14.12)**	0.01 (0.07)	0.28 (7.17)**	0.31 (7.04)**	0.17 (7.01)**
*ln*NUMPARTS	0.11 (2.02)*	0.35 (4.09)**	0.46 (6.18)**	0.17 (4.76)**	0.29 (4.01)**	0.34 (4.70)**	0.60 (5.61)**

ILCOST = Indirect Labor Cost
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* *indicates significant at the 5% level.*
** *indicates significant at the 1% level.*

Estimation results for the ARMA models appear in Tables 7 and 8. In the multiple cost driver model, we find that NUMSETUPS is significant at the 5% level for six of the seven departments, and NUMPARTS is significant for all seven departments, thus supporting our earlier inference about the significance of these cost drivers.

IV. Managerial Implications

The findings of this study are useful to managers at our research site. The results document that indirect production labor costs are driven by number of setups and number of parts, in addition to the direct labor cost based measure of production volume, and thus the findings provide a more detailed understanding of how these costs arise. More importantly, these results support their cost control efforts by providing specific estimates of the monetary impact of the number of daily setups and parts produced on indirect production labor costs that can be used to evaluate and justify cost- benefit aspects of programs to reduce these aspects of production complexity.

Ittner and Larcker (2001) assert that studies on costs need to determine whether an improved understanding of cost drivers may lead to better decision making by managers. To examine the existence of potential costing errors, we estimated the cost distortion or difference between the traditional labor based cost system and a cost model based on multiple cost drivers. Recall that our statistical analysis is based on daily indirect production labor costs and not average product costs for a year. To estimate product costs, therefore, we need to translate our daily cost estimates to average product costs. For this purpose, we first estimated the cost of each batch of parts on the day it was manufactured by inserting the actual values of the number of setups and parts produced on that day in our multiple cost driver model. We then calculated the average indirect production labor costs for each part as a weighted average of daily unit indirect production labor costs for that part based on all the batches manufactured in a year. We compared these average costs with the unit indirect production labor costs calculated using the existing method of estimating indirect production labor costs as a percentage of direct labor costs alone where the percentage factor in each department is the ratio of the total indirect production labor costs to the total direct production labor costs in the preceding year. We calculated the percentage cost difference as [(estimate based on existing method) - (estimate based on multiple cost driver model)] / [estimate based on multiple cost driver model] (Banker et al., 1990). We find that low volume parts tend to be under - costed and high volume parts tend be over-costed. Percentage cost difference for a part is significantly positively correlated ($r=0.43$, $p=0.0001$) with its annual production volume, consistent with the literature on the behavior of overhead costs.

Table 9: Errors in Cost Predictions

Panel A: Mean Absolute Percentage Errors

Department	Simple Method*	Single Driver Regression	Multiple Drivers Regression
Sheet Metal	20.36	25.16	14.20
Machine Shop	47.93	55.05	33.79
Brush & Steel Wool	39.34	46.39	39.30
Paint Shop	39.53	55.00	50.73
Component Assembly	55.32	59.58	48.90
Welding	23.54	32.01	25.96
Final Assembly	86.95	72.45	69.90

Panel B : Mean Squared Percentage Errors

Department	Simple Method*	Single Driver Regression	Multiple Drivers Regression
Sheet Metal	666.48	1157.58	357.23
Machine Shop	15074.90	26104.84	4468.52
Brush & Steel Wool	7308.71	4818.04	2576.89
Paint Shop	7053.32	44463.26	39217.46
Component Assembly	8707.42	14657.80	7705.59
Welding	1089.13	10149.26	3477.02
Final Assembly	46946.06	28694.67	24251.18

- The simple method used at our research site estimates indirect production labor costs for each production department by multiplying the daily production labor costs by the ratio of its total indirect production labor costs to its total direct production labor costs in the preceding year.

The documented violation of the fundamental assumptions underlying the existing labor- based cost accounting system suggests that many of the cost estimates based on that system may be distorted. We explore this issue by evaluating how these different methods perform in providing cost predictions useful for daily departmental production planning and budgeting. For this purpose, we re-estimated both the single and the multiple cost driver models 1 and 2 using daily data for only the first four years. We then obtained a prediction for the daily indirect production labor costs for the holdout year five for each production department based on its actual activity levels and the parameters estimates based on the first four years' data. We also predicted daily indirect production labor costs using the simple method described earlier that is currently in place at our research site. For this purpose, we multiply the daily direct production labor costs for each production department by the ratio of its total indirect production labor costs to its total direct production labor costs in the preceding year. Finally, we calculated mean absolute and squared percentage deviations for each department based on the daily cost prediction errors. Table 9 presents a comparison of the prediction errors using the three methods.

The multiple cost driver model results in the lowest mean percentage absolute and squared deviations for five of the seven departments, while the single cost driver regression model performs the worst in all but one department. More interestingly, we find that the simple method used by the company predicts daily costs almost as well as our multiple cost driver regression model. This finding can be interpreted in two different ways. First, we may infer that the simple method of forecasting indirect production labor costs as a proportion of direct labor costs performs well even when multiple factors drive these indirect costs because direct labor costs are highly correlated with these other drivers. Alternatively, we may infer that managers assign resources to indirect production labor activities in the observed manner because the existing accounting system budgets resources in proportion to direct labor costs. It is, of course, impossible to discriminate between these two alternative inferences at our research site because the same accounting system has continued to be used throughout our sample period.

Although, our findings seem to indicate that the traditional costing system performs as well as a sophisticated costing system for prediction/planning purpose, our earlier finding on cost distortions indicate that a costing system based on the hierarchy of cost drivers may be more useful for pricing, product mix and perhaps other decisions such as outsourcing. These mix results seem consistent with studies that find that only about 20% to 30% percent of firms adopt more elaborate costing systems (Innes et al. 2000; Schoute, 2011). The findings also echo the results of Ittner et al. (2002) who document that the extensive use of ABC by firms has no significant association with return on assets and that benefits may be contingent on firm characteristics.

V. Concluding Remarks

Labro (2015) recently noted that compared to research on management controls, there is little research on information to support decision making, even though this is highly relevant to business practice and teaching. In the present study, we use time-series data from seven production departments of a manufacturing company to test the assumption that indirect production labor costs are not associated with other batch-related and product-sustaining activity cost drivers such as number of setups and number of distinct parts. We also test the assumption that indirect production labor costs are proportional to direct labor costs. The assumption that indirect production labor costs are proportional to a single unit-related cost driver, such as direct labor cost, is common in most traditional cost accounting systems. Our results document a strong relation between indirect production labor costs and both number of setups and number of distinct parts, as suggested by the cost hierarchy. In addition, our empirical results rejected the proportionality assumption for all seven departments. In sum, our results suggest that indirect production labor costs are associated with multiple cost drivers, and the relation between these variables is not proportional.

Since managers make daily operating decisions based on their information, we measure the extent of product cost distortions induced by traditional labor-based cost allocations. This result provides evidence on the usefulness of activity based costing systems for managerial decision making as it documents that the product cost estimates based on the traditional system may be distorted. We then examined the predictability of the cost hierarchy model. We find that the simple method used at our research site to estimate indirect production labor costs performs remarkably well in predicting daily departmental costs. Whether this finding reflects the true underlying production and cost relation, or whether it is an artifact only of managers reacting to the existing information system remains as another direction for future research. Specifically, it will be insightful to evaluate whether and how indirect cost behavior changes when a firm changes its cost accounting system. Our result on the usefulness of cost hierarchy for cost prediction cautions that the overall impact of sophisticated costing systems on managerial decision making and firm performance may be limited, and echoes the skepticism of Dopuch (1993) and results of Ittner et al. (2002).

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