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Performance Impact of the Elimination of Direct Labor Variance Reporting: A Field Study

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ABSTRACT

Using a field study approach, we examine two competing perspectives on direct labor variance reporting: some argue that direct labor variance reporting is costly and cumbersome, and should be eliminated; whereas others contend that without direct labor variance information, managers will not be able to monitor workers effectively, causing workers to shirk and worker productivity to decline. Specifically, we investigate the productivity and quality impacts of eliminating direct labor variance reporting with panel data containing 36 months of data from seven experimental plants that eliminated direct labor variance reporting and 11 control plants that did not. The experimental plants experienced a significant decline in labor productivity compared to the control plants. Also, the experimental plants showed an improvement in product quality, indicating that workers reallocate their efforts to other tasks as a result of the change in the information set available to evaluate them.

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1. *Introduction*

In this paper, we analyze data from seven plants ("experimental plants") of a division, Protech (a pseudonym to disguise its identity), of a Fortune 500 company both before and after direct labor variance reporting was eliminated. Limited comparative data are available for 11 other plants ("control plants") at the same geographic location and with the same four-digit SIC classification, where the reporting change was not made. We investigate the 18 plants over a 36-month period from January 1991 to December 1993. The change in the direct labor variance reporting occurred for seven of the 18 plants at the end of the 24th month. A detailed description of the research site is presented in Appendix A.

Two competing perspectives on direct labor variance reporting motivate this analysis. The practitioner literature portrays direct labor variance reporting as costly and cumbersome, focusing managers on mundane details rather than on matters of strategic importance to the firm. Following the recommendation of several management consultants, many companies have now stopped reporting direct labor variances (Berlant, Browning, and Foster [1990], Clements and Spoede [1992], Johnson and Kaplan [1987], Peters and Austin [1985], Turk [1990]). On the other hand, information economics models of supervisory control suggest that, without direct labor cost variance information, managers will not be able to monitor workers as effectively, workers will shirk, and worker productivity will decline (Banker and Datar [1989], Amershi, Banker, and Datar [1990]). Lack of availability of detailed information to monitor one dimension of performance (such as productivity) may also result in the reallocation of worker effort to other dimensions (such as quality) that are monitored (Feltham and Xie [1994], Holmström and Milgrom [1991], Banker and Thevaranjan [1995]).

The results of our empirical analysis support the prediction based on information economics perspective. The seven experimental plants that stopped direct labor variance reporting experienced a substantially greater decline in labor productivity than the 11 control plants that continued the reporting. Further, the seven experimental plants experienced improvement in quality of products delivered to customers after the reporting change that was not discernable for the 11 control plants.

2. *Research Hypotheses*

Protech managers responsible for the decision to eliminate direct labor variance reporting told us that they were influenced by the recent practitioner literature suggesting that accounting reports are not useful for monitoring labor productivity because they are not timely and do not reflect

Science and Technology, University of California at Los Angeles, University of Memphis, University of Minnesota, University of Nebraska, University of Notre Dame, University of Pennsylvania, University of Rochester, The University of Texas at Dallas, and University of Washington. The paper has benefited from the comments of participants at these forums.

the right measures (Johnson and Kaplan [1987], Howell and Soucy [1987], Peters and Austin [1985]).[1] Many plants at other companies implementing just-in-time (JIT) and quality improvement programs use non-financial performance measures such as quality, flexibility, and lead time (Banker, Potter, and Schroeder [1993]). Foster and Horngren [1988] find that reporting direct labor variances creates incentives for individual workers to ignore the effect of their actions on other workers and production cells, and has a detrimental effect in a JIT environment, where the emphasis is on total plant performance. According to Turk [1990], preoccupation with direct labor variances results in an inappropriate focus on direct labor utilization at the expense of other strategically important performance dimensions.

Information economics models of performance evaluation provide a theoretical perspective for this experiment. Protech managers used direct labor variance reports to evaluate worker productivity, and thus as a tool for monitoring and control. Eliminating the reports decreases the precision of information available to a manager (principal) about the actions of the worker (agent). If the manager does not compensate by increased direct monitoring, some workers may shirk. Unavailability of separate direct labor variances by job makes it difficult for managers to identify such shirking individuals with low productivity. Many production supervisors we interviewed emphasized that there is no replacement for the hard documentation in an accounting variance report for evaluating and dealing with workers. They also stated that direct observation of the many workers throughout a shift is difficult, and provides at best an imperfect signal about their productivity.

We cannot determine whether managers increased direct monitoring after the reporting change, because we did not begin our study until after the change had been implemented. Managers do not maintain any reliable records of direct monitoring. Also, we cannot simply ask managers about their behavior before and after the reporting change because retrospective elicitation of perceptions comparing two past periods is unreliable (Bazerman [1994]).[2]

Protech workers are evaluated on their productivity and quality improvement. In an agency theoretic context, reducing the productivity information available to managers, holding the quality information constant implies an

[1] Johnson and Kaplan [1987, p. 188] state: "In one instance, we saw a plant where 65% of its general ledger computer code processed direct labor transactions even though direct labor represented only 4% of total costs." Direct shopfloor labor costs at Protech comprised about 27% (=80% of 33.5%) of manufacturing costs.

[2] There are two possible sources of bias in judgement that are likely to result in interviewed managers reporting that the frequency of their direct monitoring of workers was higher in recent months. First, "ease-of-recall" bias occurs because recent events are easier to recall, and individuals judge these events to be more frequent than events of equal frequency that are less recent (Bazerman [1994, p. 45]; Fischoff [1975], [1980]). Second, "hindsight bias" occurs knowing the outcome, individuals tend to overestimate a presumed causal relation in recalling and judging a past event as it appeared to them before learning of the outcome (Bazerman [1994, p. 18]; Tversky and Kahneman [1975]).

increase in the relative importance of performing on the quality dimension. Workers would be expected to redirect efforts from productivity to quality improvement, resulting in decreased productivity and increased quality (Banker and Thevarajan [1995]). Intuitively, a noisier signal for productivity results in less productivity effort. The noisy productivity signal results in a lower productivity effort which, for a convex disutility function for *total* effort, reduces the marginal disutility of quality effort, leading to an increase in this effort. This prediction is consistent with the notion from the practitioner literature (Green, Amenkhienan, and Johnson [1991], Howell and Soucy [1987], Berlant, Browning, and Foster [1990], Foster and Horngren [1988]) that eliminating direct labor variance reporting alleviates the preoccupation of managers and workers with labor productivity and focuses them on other strategic performance criteria such as quality. Therefore, we specify the following two hypotheses:

H1: *Ceteris paribus*, the elimination of direct labor variance reporting leads to lower labor productivity.

H2: *Ceteris paribus*, the elimination of direct labor variance reporting leads to higher product quality.

3. *Data and Model Specification*

3.1 DEPENDENT VARIABLES: PRODUCTIVITY

We focus on the labor productivity measure reported monthly to Protech plant managers. For the seven experimental plants, we also consider a total factor productivity measure disaggregated into partial productivity measures for each factor of production, such as labor and materials.[3] Because direct material cost data are not recorded separately for the 11 control plants, we consider a total productivity measure based on value-added for these plants (Adler [1990]).

Labor productivity (*PRDTVT*). At Protech, labor productivity is defined as follows:

$$PRDTVT = \frac{\text{Standard Direct Labor Hours}}{\text{Actual Total Shopfloor Labor Hours}} \tag{1}$$

Protech managers view the numerator as an aggregate measure of actual output (weighted sum of actual volume of different products, where the weights are standard requirements for direct labor for each product) and the denominator as a measure of actual shopfloor labor input (Hayes and Clark [1985]). Standards were generally stable during the period of our study. Standard direct labor hours are based on the established standards

[3] We focus on productivity measures that relate physical outputs to inputs. Productivity may be measured alternatively by relating all outcomes of the production process, including quality, to input resources. We evaluate quality impacts separately in section 4 while assessing the overall managerial significance of the reporting change.

and the actual production volume and, therefore, it was possible to compute standard hours for the seven experimental plants even after tracking of actual direct labor hours by production job was eliminated. Actual total shopfloor labor hours information was available from payroll timecards.

To focus on the difference in productivity before and after the reporting change, we normalize labor productivity for each plant, i, $i = 1, \ldots, 18$, by dividing its labor productivity in month t, $t = 1, \ldots, 36$, by its average labor productivity over the 24 months before the reporting change:

$$PRDTVT_{it} = \frac{\text{Labor Productivity}_{it}}{\text{Average Labor Productivity}_i} \tag{2}$$

This and other similar normalizations also enable us to mask competitively sensitive raw data.

Total factor productivity (*TFP*). The labor productivity measure *PRDTVT* is a partial productivity measure; no appreciable changes occurred during our sample period in other inputs, which can be substituted for labor. However, to evaluate the overall impact of the reporting change for the seven experimental plants, we also consider a total factor productivity measure employed by Craig and Harris [1973], Sumanth [1984], Hayes and Clark [1985], Adler [1990], and Ittner [1994]. The *TFP* measure given below for plant i is a ratio of a Paasche index of monthly output to a Paasche index of five inputs: labor, manufacturing support, materials, capital, and energy:

$$TFP_{it} = \frac{\sum_r p_{ir}^0 y_{ir}^t}{\sum_n w_{in}^0 x_{in}^t} \tag{3}$$

where, y_{ir}^t is the number of units of product r manufactured in plant i in month t, p_{ir}^0 is the standard cost per unit of product r in plant i in the last month ($t = 36$) in our sample, x_{in}^t is the quantity of input n consumed in plant i in month t, and w_{in}^0 is the cost per unit of input n in the last month ($t = 36$). We normalized the *TFP* measure (and partial productivity measures described below) by dividing the monthly productivity measure by the average productivity for the first 24 months as in equation (2) above. We computed total productivity for the 11 control plants similarly except that materials cost was excluded from the denominator and the standard unit cost for each product in the numerator reflected only conversion cost.

We collected output quantity data from monthly manufacturing reports and standard cost information from accounting records. The payroll department provided labor hours and average wage rate data. We collected manufacturing support, materials and energy cost data from monthly manufacturing cost statements, and adjusted them to month 36 price levels using company specific inflation indexes provided by Protech. Following Adler [1990] and Ittner [1994], we estimated capital costs based on the book value of plant and equipment and a real cost of capital of 7%, reflecting the long run average inflation adjusted cost of a typical mix of debt and equity.

Partial productivity (*PPLABOR*, *PPMATL*, *PPOVRHD*). The inverse of total factor productivity is an additively separable function of the inverses of its component partial productivity measures (Craig and Harris [1973]). We compute a partial productivity measure for each input n, $n =$ labor, materials, and overhead (=support + capital + energy), for each experimental plant i in a month t as follows:

$$PPn_{it} = \frac{\sum_r p^0_{ir} y^t_{ir}}{w^0_{in} x^t_{in}} \tag{4}$$

We aggregate capital and energy inputs with manufacturing support because they are relatively insignificant. Analysis of separate partial productivity measure for each of these three inputs yielded no new insights.

The *PPLABOR* measure differs from the earlier *PRDTVT* measure because its numerator aggregates the output quantities as a weighted sum of output quantities using standard product costs as weights instead of standard direct labor hours as weights. The denominators for the two labor productivity measures differ by the constant multiplier w^0_{in} representing the month 36 wage rate, which cancels out when we normalize as in equation (2).

3.2 DEPENDENT VARIABLES: QUALITY

For the seven experimental plants, data are available for two measures of internal quality: quality audit yield rate and scrap-rework cost percentage; and for three measures of external quality: customer rejects at delivery inspection, customer returns on installation, and customer returns under long term warranty.[4] Protech managers monitor *customer returns on installation* particularly closely because it has a direct impact on customer satisfaction. There was no change in the reporting of any of the quality measures during the sample period.

Quality audit yield rate (*QAUDYLD*). This quality measure is proportion of product units found to be defective during quality audit inspection. As with the productivity ratios, we normalized the yield rate for each plant by dividing by the average rate over the first 24 months (before the reporting change). We normalized all other quality measures in the same way.

Scrap and rework cost percentage (*SCRAP*). We used accounting records to compute monthly scrap and rework costs as a percentage of total direct material cost for each plant.

Customer rejects on inspection (*INSPNREJ*). Customer rejections occur because of errors in communicating customer orders and instructions, or errors in packing; these are unrelated to product defects. Protech management informed us that most of the production is against customer orders, and the lag between production and rejection is usually less than one month. A test check of plant records confirmed this assertion. We normalize first

[4] The broad spectrum of quality indicators used at the seven experimental plants at Protech, spans most of the elements tracked commonly by companies evaluating their quality costs (Ittner [1996, table I, p. 118)]. Consistent with the majority of the firms in Ittner's sample, Protech did not maintain separate data for preventive maintenance, quality-related wait time, liability claims, excess inventory, or quality-related overtime.

by dividing the number of customer rejects on inspection for a plant in a month $t+1$ by the plant's production volume for month t, assuming a one-month lag between production and customer rejects. Our results do not change appreciably when we use lags of zero or two months.

Customer returns on installation (*INSTLRET*). Protech customers are principally original equipment manufacturers (OEMs) who install Protech products in equipment, machines, systems or building units manufactured. These customers usually detect product failure only on installation. Therefore, this is the one external quality measure that best reflects product defect rate, and Protech managers monitor it more closely than any other quality measure. Sampling of customer returns data indicated that over 95% of the returns occur within two months of production. As in the case of *INSPNREJ*, we present results assuming a lag of one month between production and rejection, but the results are robust to assumed lags of zero or two months also.[5]

Warranty returns (*WARNTRET*). Returns under extended warranty can occur over 18 months. Therefore, warranty returns rate cannot be matched easily with the production for a specific month. Protech management also is primarily interested in the long term trend in warranty returns. Therefore, we do not expect much impact on monthly warranty returns rate in the 12 months following the reporting change. The results we report assume a one-month lag, but are robust to other lag assumptions.

Reject rate (*REJECTS*) *for control plants.* Only one measure of quality is required at the 11 control plants. Their certified supplier-type relation with their customers requires inspection of all production. Checks or rejects at the customers' plants are very rare, and no external quality measures are required. Therefore, only the *REJECTS* measure is monitored at these plants, based on the reject rate resulting from the 100% inspection. This reject rate measure for the control plants corresponds to the entire spectrum of internal and external measures for the experimental plants where only a sample is inspected (generating the *QAUDYLD* measure) leaving the possibility of customers discovering defects and rejecting the product (generating the *INSTLRET* measure).

3.3 CONTROL VARIABLES

Manufacturing performance may be affected by factors other than a reporting change. *Structural factors* represent choices about underlying structure, such as scale, experience, and capacity utilization. *Executional factors* represent managerial policies related to equipment, inventory, workforce, and confusion in operations. We reviewed prior research (Hayes and Clark [1985], Katz, Kochan, and Keefe [1987], Ichniowski, Shaw, and Prennushi [1997], Kelley [1994], Ittner and MacDuffie [1995]) and consulted Protech managers and supervisors to identify structural and executional factors that

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[5] Customer rejects capture only defects sufficiently bad to cause rejection. Devices manufactured by Protech are high-value items and play a critical role in the systems assembled by the OEMs and, therefore, if a device does not work then the customer *must* reject it.

need to be controlled in order to assess the impact of eliminating direct labor variance reporting. We identified one structural factor, production volume (*VOLUME*), as one of the control variables. The executional factors that we identified as control variables are: overtime (*OVTIME*), turnover (*ADDN*), positive and negative fluctuations in production volume (*PFLUCT*, *NFLUCT*). We also identified seasonal factors peculiar to our research setting as control variables: Winter (*QUARTER1*), Summer (*QUARTER2*), Fall (*QUARTER3*), and Spring (*QUARTER4*). A detailed description of the control variables and the process of identifying them is presented in Appendix B.

3.4 DESCRIPTIVE STATISTICS

We present descriptive statistics for the variables before and after the reporting change separately for experimental and control plants in tables 1 and 2, respectively. Analysis of correlations between the variables (not reported) indicates that the two partial labor productivity measures are positively correlated with each other and with the total factor productivity measure for both the experimental and control plants (these correlations are between 0.4 and 0.6 with $p < 0.01$). Production volume is positively correlated with both partial labor productivity measures, the total productivity measure, and the partial productivity measure for overhead. For the experimental plants, there is relatively low correlation between the different quality measures.

3.5 MODEL SPECIFICATION

We estimate two separate fixed effects models, one by pooling observations for the seven experimental plants, and another for the 11 control plants.[6] The model pooling the experimental plants is:

$$\begin{aligned} PRDTVT_{it} = {} & \alpha_1 P1_{it} + \alpha_2 P2_{it} + \cdots\cdots + \alpha_7 P7_{it} + \beta_1 REPCHG_{it} \\ & + \beta_2 VOLUME_{it} + \beta_3 WIP_{it} + \beta_4 OVTIME_{it} + \beta_5 ADDN_{it} \\ & + \beta_6 PFLUCT_{it} + \beta_7 NFLUCT_{it} + \beta_8 QUARTER2_{it} \\ & + \beta_9 QUARTER3_{it} + \beta_{10} QUARTER4_{it} + \varepsilon_{it}; \\ & \quad i = 1, \ldots, 7 \text{ experimental plants and } t = 1, \ldots, 36 \text{ months.} \end{aligned} \tag{5}$$

The model for the control plants ($i = 1, \ldots, 11$) is similar except that 11 dummy variables ($P1_{it}, \ldots, P11_{it}$) now identify the 11 control plants. Similar fixed effects models are also specified for other productivity variables (*TFP*, *PLABOR*, *PPMATL*, *PPOVRHD*) and quality variables (*QAUDYLD*, *SCRAP*, *INSPNREJ*, *INSTRET*, *WARNRET*, *REJECTS*) by replacing the left hand side of equation (5) by the appropriate measure.

[6] Our results are robust to pooling all 18 plants in one model with two different *REPCHG* coefficients for experimental and control plants.

TABLE 1

Comparison of Variables Before and After the Change in Direct Labor Variance Reporting for the 7 Experimental Plants. In this Field Experiment to Examine the Performance Impact of the Elimination of Direct Labor Variance Reporting, We Analyzed Data From 7 Experimental Plants of a Division of a Fortune 500 Company Both Before and After the Reporting Change Was Made. We Also Analyzed Limited Comparative Data From 11 Control Plants at the Same Geographic Location With the Same Four Digit SIC Classification, Where the Reporting Change Was Not Made. The Reporting Change Occurred in the 7 Experimental Plants at the End of the 24th Month of a 36-Month Study Period

	24 Months Before the Reporting Change		12 Months After the Reporting Change		
Variables	Mean	Standard Deviation	Mean	Standard Deviation	t-statistics
Dependent Variables					
Normalized[@] Labor Productivity	1.000	0.124	0.885	0.115	−1.801
Normalized Total Factor Productivity	1.000	0.109	0.992	0.166	−0.106
Normalized Partial Labor Productivity	1.000	0.170	0.882	0.220	−1.123
Normailized Partial Overhead Productivity	1.000	0.414	1.122	0.605	0.440
Normalized Partial Material Productivity	1.000	0.096	1.045	0.205	0.526
Quality Yield Rate (Percentage of Products Passing Quality Audit)	1.000	0.025	1.010	0.022	0.794
Scrap and Rework Cost as Percentage of Material Cost	1.000	0.983	1.478	1.838	0.607
Customer Rejects on Inspection in Month $t+1$ as Percentage of Production Volume in Month t	1.000	3.084	1.070	3.022	0.043
Customer Returns on Installation in Month $t+1$ as Percentage of Production Volume in Month t	1.000	2.078	0.495	0.774	−0.602
Warranty Returns in Month $t+1$ as Percentage of Production Volume in Month t	1.000	1.846	0.958	1.057	−0.052
Independent Variables					
Normalized Production Volume	1.000	0.357	1.042	0.368	0.217
Work-in-Process Inventory as Percentage of Product Cost	1.000	0.231	1.139	0.433	0.749
Overtime (Normalized Ratio of Overtime Labor Hours to Total Labor Hours)	1.000	0.487	1.936	1.044	2.150
Turnover (Normalized Ratio of New Employees to Total Employee Headcount)	1.000	1.071	1.241	0.982	0.439
Positive Fluctuations in Production Volume (Normalized Percentage Increase in Production Volume in Month t Relative to Month $t-1$)	1.000	1.389	0.978	1.390	−0.030
Negative Fluctuations in Production Volume (Normalized Percentage Decrease in Production Volume in Month t Relative to Month $t-1$)	1.000	1.903	1.015	1.848	0.015

[@]All normalizations are performed by dividing by the average of the first 24 months (i.e., data before the reporting change).

TABLE 2

Comparison of Variables Before and After the Change in Direct Labor Variance Reporting for the 11 Control Plants. In this Field Experiment to Examine the Performance Impact of the Elimination of Direct Labor Variance Reporting, We Analyzed Data From 7 Experimental Plants of a Division of a Fortune 500 Company Both Before and After the Reporting Change Was Made. We Also Analyzed Limited Comparative Data From 11 Control Plants at the Same Geographic Location With the Same Four Digit SIC Classification, Where the Reporting Change Was Not Made. The Reporting Change Occurred in the 7 Experimental Plants at the End of the 24^{th} Month of a 36-Month Study Period

Variables	24 Months Before the Reporting Change		12 Months After the Reporting Change		
	Mean	Standard Deviation	Mean	Standard Deviation	*t*-statistics
Dependent Variables					
Normalized[@] Labor Productivity	1.000	0.123	0.980	0.125	−0.378
Normalized Total Factor Productivity	1.000	0.216	1.065	0.185	0.758
Normalized Partial Labor Productivity	1.000	0.310	0.967	0.445	−0.202
Normalized Partial Overhead Productivity	1.000	0.404	1.053	0.387	0.314
Reject Rate (Cost of Products Rejected as Percentage of Product Cost in Control Plants)	1.000	1.709	1.179	3.285	0.160
Independent Variables					
Normalized Production Volume	1.000	0.363	0.992	0.404	−0.049
Work-in-Process Inventory as Percentage of Product Cost	1.000	0.202	0.897	0.167	−1.303
Overtime (Normalized Ratio of Overtime Labor Hours to Total Labor Hours)	1.000	0.667	1.103	0.621	0.375
Turnover (Normalized Ratio of New Employees to Total Employee Headcount)	1.000	1.761	0.897	0.826	−0.176
Positive Fluctuations in Production Volume (Normalized Percentage Increase in Production Volume in Month t Relative to Month $t-1$)	1.000	1.423	1.007	1.387	0.012
Negative Fluctuations in Production Volume (Normalized Percentage Decrease in Production Volume in Month t Relative to Month $t-1$)	1.000	1.752	1.049	1.770	0.065

[@]All normalizations are performed by dividing by the average of the first 24 months (i.e., data before the reporting change).

4. *Results and Discussion*

4.1 DIAGNOSTICS

Durbin-Watson test statistics and estimates of autocorrelation coefficients obtained by analyzing the residual terms for each plant indicated the presence of serial correlation in the models for *TFP*, *PPMATL*, and the quality measures. To correct for these effects, we transformed the data using the Park and Mitchell [1980] version of the Prais-Winsten estimator.[7] Analyses of the transformed data indicated no serious serial correlation. White's test did not indicate any significant heteroskedasticity problem; a Kolmogorov-Smirnov test indicated no violations of the normality assumption. Identifying outliers and influential observations using the Belsley-Kuh-Welsch [1980] criteria, we repeated our analysis after deleting such observations and obtained results similar to those reported. Finally, variance inflation factors and Belsley-Kuh-Welsch [1980] condition indices did not indicate any multicollinearity problems.

4.2 RESULTS FOR LABOR PRODUCTIVITY

Estimation results for the *PRDTVT* model appear at the top of table 3. The coefficient for the reporting change variable is negative and significant for the experimental plants ($p < 0.01$, two-tail), indicating a decline in labor productivity of 11.0% on average after the reporting change. The other significant variables in the model are volume, positive fluctuations in production, and Summer and Fall quarters ($p < 0.01$, two-tail). The sign and significance of these variables indicate that labor productivity has a positive relation with production volume, and negative relations with seasonal distractions, and positive fluctuations that reflect departure from the norm. The reporting change variable is not significant in the model estimated for the control plants ($p = 0.29$, two-tail).

4.3 RESULTS FOR TOTAL AND PARTIAL PRODUCTIVITY MEASURES

Table 3 also displays estimation results for the models explaining variations in *TFP* and the three partial productivity measures for labor, materials, and overhead. The coefficient of the reporting change variable is significant and negative in the *TFP* and *PPLABOR* regressions for the experimental plants ($p < 0.01$, two-tail), but not for the control plants ($p = 0.78$ and $p = 0.58$, respectively, two-tail).[8] These results are consistent with our earlier finding that labor productivity declined after the reporting change for the experimental plants but not for the control plants. As before, the magnitude

[7] The Prais-Winsten transformation involves converting the first observation for every time series as follows: transformed $X = \sqrt{(1-\rho^2)} * X$ where X is a given data point and ρ is the autocorrelation coefficient. Further, all other observations of the time series are transformed as follows: transformed $X = X - \rho *$ (lagged value of X).

[8] The results are very similar for these regressions when we compute the total productivity measure for the experimental plants after excluding direct material costs to make the measure directly comparable to the total productivity measure available for the control plants.

TABLE 3

Estimation Results for Fixed Effects Models Examining the Impact of Eliminating Direct Labor Variance Reporting on Productivity Measures. The Reporting Change Occurred in the 7 Experimental Plants at the End of the 24th Month during a 36-Month Study Period. (t-statistics in Parentheses)*

Dependent Variable (*DEPVAR*)	Group	Direct Labor Variance Reporting Change (*REPCHG*)	Production Volume (*VOLUME*)	Work-in-Process (*WIP*)	Overtime (*OVTIME*)	Turnover (*ADDN*)	Positive Fluctuations in Production Volume (*PFLUCT*)	Negative Fluctuations in Production Volume (*NFLUCT*)	Summer Quarter Dummy (*QUARTER2*)	Fall Quarter Dummy (*QUARTER3*)	Spring Quarter Dummy (*QUARTER4*)	R^2
Labor Productivity (*PRDTVT*)	Experimental	−0.110	0.098	−0.027	−0.003	−0.008	−0.015	−0.003	0.030	−0.054	−0.085	0.988
		(−5.82)	(3.63)	(−1.05)	(−0.28)	(−1.21)	(−2.61)	(−0.69)	(1.61)	(−2.73)	(−4.51)	
	Control	−0.014	0.108	0.035	0.026	0.007	−0.013	−0.006	0.005	−0.029	−0.020	0.987
		(−1.07)	(5.25)	(1.06)	(2.57)	(1.75)	(−2.41)	(−1.55)	(0.29)	(−1.90)	(−1.32)	
Total Factor Productivity (*TFP*)	Experimental	−0.103	0.135	0.117	0.041	−0.011	−0.009	0.001	0.055	−0.154	−0.101	0.981
		(−4.22)	(3.87)	(3.51)	(2.58)	(−1.26)	(−1.26)	(0.08)	(2.27)	(−6.01)	(−4.18)	
	Control	0.005	0.818	0.186	−0.035	−0.001	0.039	−0.017	−0.002	0.038	0.099	0.980
		(0.28)	(29.39)	(−4.12)	(−2.52)	(−0.16)	(5.56)	(−3.34)	(−0.11)	(1.85)	(4.85)	
Partial Labor Productivity (*PPLABOR*)	Experimental	−0.109	0.103	−0.073	−0.011	0.020	0.020	0.005	−0.053	−0.001	−0.097	0.970
		(−3.46)	(2.34)	(−1.73)	(−0.53)	(1.75)	(2.07)	(0.60)	(−1.71)	(−0.03)	(−3.16)	
	Control	−0.015	0.758	0.123	−0.109	−0.005	0.034	−0.022	−0.007	0.185	0.072	0.955
		(−0.55)	(17.76)	(1.78)	(−5.14)	(−0.58)	(3.08)	(−2.82)	(−0.22)	(5.81)	(2.27)	
Partial Overhead Productivity (*PPOVRHD*)	Experimental	−0.051	0.219	0.309	0.106	−0.016	0.028	0.013	0.001	−0.255	−0.064	0.866
		(−0.65)	(2.03)	(2.96)	(2.10)	(−0.57)	(1.19)	(0.71)	(0.01)	(−3.13)	(−0.85)	
	Control	0.014	0.860	0.369	0.011	0.001	0.044	−0.013	0.001	−0.062	0.118	0.959
		(0.54)	(20.49)	(−5.42)	(0.52)	(0.04)	(4.03)	(−1.74)	(0.02)	(−1.99)	(3.82)	
Partial Material Productivity (*PPMATL*)	Experimental	0.055	0.001	−0.001	−0.028	−0.302	0.003	0.008	−0.014	−0.035	−0.062	0.941
		(1.61)	(1.49)	(−0.92)	(−1.30)	(−1.97)	(0.34)	(0.91)	(−0.43)	(−1.04)	(−1.84)	

*$DEPVAR_{it} = (\alpha_1 P1_{it} + \alpha_2 P2_{it} + \cdots \alpha_n Pn_{it}) + \beta_1 REPCHG_{it} + \beta_2 VOLUME_{it} + \beta_3 WIP_{it} + \beta_4 OVTIME_{it} + \beta_5 ADDN_{it} + \beta_6 PLUCT_{it} + \beta_7 NFLUCT_{it} + \beta_8 QUARTER2_{it} + \beta_9 QUARTER3_{it} + \beta_{10} QUARTER4_{tit} + \varepsilon_{it}$; $i = 1, \ldots, 7$ for experimental plants, $i = 1, \ldots, 11$ for control plants, $t = 1, \ldots, 36$ months where, $P1_{it}, \ldots, Pn_{it}$ are dummy variables that indicate the identity of each plant i in month t ($n = 7$ for experimental plants and 11 for control plants).

of the reporting change coefficient is an indication, in percentage terms, of the impact of reporting change on a given productivity or quality metric, all else being equal. The reporting change variable is not significant in the overhead or the materials model ($p = 0.52$ and $p = 0.11$, respectively, two-tail). Thus, the empirical evidence indicates that eliminating direct labor reporting leads to lower labor productivity.[9]

We repeated the estimation with separate dummy variables for five of the six six-month periods in our sample, instead of the single dummy for *REPCHG*. Specifically, we estimate:

$$\begin{aligned} PRDTVT_{it} = {} & \alpha_1 P1_{it} + \alpha_2 P2_{it} + \cdots\cdots + \alpha_7 P7_{it} + \gamma_1 D712_{it} \\ & + \gamma_2 D1318_{it} + \gamma_3 D1924_{it} + \gamma_4 D2530_{it} + \gamma_5 D3136_{it} \\ & + \beta_2 VOLUME_{it} + \beta_3 WIP_{it} + \beta_4 OVTIME_{it} + \beta_5 ADDN_{it} \\ & + \beta_6 PFLUCT_{it} + \beta_7 NFLUCT_{it} + \beta_8 QUARTER2_{it} \\ & + \beta_9 QUARTER3_{it} + \beta_{10} QUARTER4_{it} + \varepsilon_{it}; \\ & \quad i = 1, \ldots, 7 \text{ experimental plants; } t = 1, \ldots, 36 \text{ months.} \end{aligned} \tag{6}$$

where $D712 = 1$ for months 7 to 12, 0 otherwise; $D1318 = 1$ for months 13 to 18, 0 otherwise; $D1924 = 1$ for months 19 to 24, 0 otherwise; $D2530 = 1$ for months 25 to 30, 0 otherwise; $D3136 = 1$ for months 31 to 36, 0 otherwise; and analogous models for other dependent variables. For the *PRDTVT* model, $\gamma_1 = -0.026$ ($t = -0.56$), $\gamma_2 = -0.039$ ($t = -1.50$), $\gamma_3 = -0.095$ ($t = -2.08$), $\gamma_4 = -0.151$ ($t = -5.37$) and $\gamma_5 = -0.187$ ($t = -3.89$). The F-statistic for each of the seven hypothesis tests $\gamma_4 = \gamma_1$, $\gamma_4 = \gamma_2$, $\gamma_4 = \gamma_3$, $\gamma_5 = \gamma_1$, $\gamma_5 = \gamma_2$, $\gamma_5 = \gamma_3$ and $\gamma_4 + \gamma_5 = \gamma_2 + \gamma_3$ is significant at the 1% level, while the hypotheses that $\gamma_3 = \gamma_2$ and $\gamma_5 = \gamma_4$ cannot be rejected even at the 10% level. Thus, the estimation results indicate that the decline in labor productivity during each of the two six-month periods after the reporting change, relative to any of the four six-month periods before the change, is statistically significant.

4.4 RESULTS FOR QUALITY MEASURES

Table 4 displays results for the five quality measures for the experimental plants and the one quality measure for the control plants. The reporting change variable is significant and positive for the *QAUDYLD* regression ($p < 0.01$, two-tail), and negative for the *INSTLRET* regression ($p = 0.02$, two-tail), and not significant for the other three models corresponding to *SCRAP*, *INSPREJ*, and *WARNRET* for the experimental plants ($p = 0.17$, 0.52, and 0.98, respectively, two-tail), signaling overall an improvement in quality

[9] When we estimated the labor productivity models with scrap as an additional explanatory variable, the coefficient estimates did not change appreciably.

TABLE 4

Estimation Results for Fixed Effects Models Examining the Impact of Eliminating Direct Labor Variance Reporting on Quality Measures. The Reporting Change Occurred in the 7 Experimental Plants at the End of the 24th Month during a 36-Month Study Period. (t-statistics in parentheses)*

Dependent Variable (*DEPVAR*)	Direct Labor Variance Reporting Change (*REPCHG*)	Production Volume (*VOLUME*)	Work-in-Process (*WIP*)	Overtime (*OVTIME*)	Turnover (*ADDN*)	Positive Fluctuations in Production Volume (*PFLUCT*)	Negative Fluctuations in Production Volume (*NFLUCT*)	Summer Quarter Dummy (*QUARTER2*)	Fall Quarter Dummy (*QUARTER3*)	Spring Quarter Dummy (*QUARTER4*)	R^2
Experimental Plants											
Quality Audit Yield Rate (*QAUDYLD*)	0.009	0.003	0.011	−0.002	−0.002	0.003	0.003	−0.011	−0.012	−0.017	0.997
	(2.85)	(0.49)	(1.24)	(−0.85)	(−1.64)	(2.91)	(3.04)	(−3.53)	(−3.17)	(−4.92)	
Scrap and Rework Percentage (*SCRAP*)	0.302	−0.820	−0.026	0.230	0.040	0.081	0.085	−0.480	0.546	0.014	0.527
	(1.38)	(−2.63)	(−0.08)	(1.63)	(0.49)	(1.18)	(1.70)	(−2.20)	(2.37)	(0.07)	
Customer Rejects on Inspection (*INSONREJ*)	0.340	−0.967	−1.218	−0.159	0.426	0.069	−0.072	0.280	−0.559	−0.343	
	(0.64)	(−1.28)	(−1.67)	(−0.46)	(2.14)	(0.41)	(−0.59)	(0.53)	(−1.00)	(−0.65)	0.157
Customer Returns on Installation (*INSTREJ*)	−0.721	−0.218	0.996	0.063	0.110	0.141	−0.071	−0.199	0.538	0.085	0.251
	(−2.37)	(−0.50)	(2.40)	(0.32)	(0.97)	(1.48)	(−1.02)	(−0.66)	(1.69)	(0.28)	
Warrranty Returns (*WARNRET*)	−0.005	−0.153	1.041	−0.181	0.585	−0.038	−0.067	0.323	−0.392	−0.058	0.400
	(−0.02)	(−0.38)	(2.68)	(−0.99)	(5.57)	(−0.42)	(−1.05)	(1.08)	(−1.27)	(−0.21)	
Control Plants											
Reject Rate (*REJECTS*)	0.262	−0.511	0.151	−0.330	0.040	0.028	0.158	−0.261	0.062	0.113	0.200
	(0.90)	(−1.20)	(0.20)	(−1.44)	(0.46)	(0.24)	(1.87)	(−0.75)	(0.18)	(0.33)	

*$DEPVAR_{it} = (\alpha_1 P1_{it} + \alpha_2 P2_{it} + \cdots \alpha_n Pn_{it}) + \beta_1 REPCHG_{it} + \beta_2 VOLUME_{it} + \beta_3 WIP_{it} + \beta_4 OVTIME_{it} + \beta_5 ADDN_{it} + \beta_6 PLUCT_{it} + \beta_7 NFLUCT_{it} + \beta_8 QUARTER2_{it} + \beta_9 QUARTER3_{it} + \beta_{10} QUARTER4_{tit} + \varepsilon_{it}$; $i = 1, \ldots, 7$ for experimental plants, $i = 1, \ldots, 11$ for control plants, $t = 1, \ldots, 36$ months where, $P1_{it}, \ldots, Pn_{it}$ are dummy variables that indicate the identity of each plant i in month t ($n = 7$ for experimental plants and 11 for control plants).

after the reporting change. The reporting change variable is not significant in the *REJECTS* regression for the control plants ($p = 0.37$, two-tail). Since *INSTLRET* is a key quality measure, the empirical evidence supports our second hypothesis that quality has improved for the experimental plants after the elimination of separate direct labor reporting while quality levels remained unchanged for the control plants.

4.5 ALTERNATIVE MODEL SPECIFICATION

Because there may be differences across plants that are masked by the pooled results reported in tables 3 and 4, we estimated a separate regression for each plant relaxing the assumption of identical coefficients across plants.[10] There may also be contemporaneous correlation among the residuals for different plants because of common factors that tend to affect all plants similarly. In such cases, OLS coefficients are unbiased and consistent but inefficient, and the estimates of their variances could be biased (Parks [1967]). Therefore, we employ the following system of seemingly unrelated regressions (SUR) to obtain more efficient estimates of the parameters in the presence of contemporaneous correlation:

$$\begin{aligned} PRDTVT_{it} &= \beta_{0i} + \beta_{1i}REPCHG_{it} + \beta_{2i}VOLUME_{it} + \beta_{3i}WIP_{it} + \beta_{4i}OVTIME_{it} \\ &\quad + \beta_{5i}ADDN_{it} + \beta_{6i}PFLUCT_{it} + \beta_{7i}NFLUCT_{it} + \beta_{8i}QUARTER2_{it} \\ &\quad + \beta_{9i}QUARTER3_{it} + \beta_{10i}QUARTER4_{it} + \varepsilon_{it}; \\ &\qquad i = 1, \ldots, 7 \text{ for experimental plants,} \\ &\qquad i = 1, \ldots\ldots, 11 \text{ for control plants, and } t = 1, \ldots, 36. \end{aligned} \tag{7}$$

Similar SUR models are also specified for other productivity and quality variables by replacing the left hand side of equation (7) by appropriate measures.

Estimation results for the SUR models (not presented here) are consistent with the fixed effects model estimates discussed above. The reporting change variable has a negative coefficient for six of the seven experimental plants for the *PRDTVT* and the *TFP* models, negative for all seven plants for the *PPLABOR* and the *INSTLRET* models, and positive for six of the seven plants for the *QAUDYLD* model. F-tests reject the hypothesis that the averages of the reporting change coefficients for the seven experimental plants are zero for the *PRDTVT*, *TFP*, *PPLABOR*, *QAUDYLD*, and *INSTLRET* models ($p < 0.01$), but not for the other models. F-tests do not reject the hypothesis that the averages of the reporting change coefficients for the

[10] The fixed effects model's restriction of equality of parameters across plants is relaxed when the SUR model is estimated. However, the SUR model required the estimation of $8 \times 8 = 144$ regression coefficients (excluding covariance matrix parameters) with $36 \times 18 = 648$ observations, an average of 1 parameter of 4.5 observations. Therefore, we consider results from both the fixed effects and the SUR models to assess the robustness of our inferences.

11 control plants are zero for the *PRDTVT*, *TFP*, *PPLABOR*, *PPOVRHD* and *REJECTS* models at the 10% significance level.[11]

4.6 ROBUSTNESS OF RESULTS

Plant specific SUR coefficient estimation indicates that one control plant exhibits a statistically significant *improvement* in labor productivity ($p = 0.03$, two-tail). To examine the influence of this plant in the control sample results, we re-estimate the fixed-effects and SUR models after deleting these observations. The results for the reporting change variable in the fixed-effects model are: $\hat{\beta} = -0.019$, ($t = -1.348$), Prob. $> |t| = 0.1784$. In the SUR model, the F-statistic for the hypothesis $\sum \beta_i = 0$ (average reporting change impact for the remaining 10 plants) is 3.46 with Prob. $> F = 0.0640$.

We also test for the difference in the estimated reporting change impact between the experimental and the control plants. The difference $[\hat{\beta}_{EXPMTL} - \hat{\beta}_{CONTROL} = (-0.110) - (-0.014) = -0.096]$ in the fixed-effects model is significantly different from zero, with F-statistic $= 18.12$ and Prob. $> F = 0.0001$. When we delete the control plant with a significant productivity increase ($p = 0.03$, two-tail), the difference $[\hat{\beta}_{EXPMTL} - \hat{\beta}_{CONTROL} = (-0.110) - (-0.019) = -0.091]$ is once again significantly different from zero, with F-statistic $= 16.272$ and Prob. $> F = 0.0001$. The hypothesis $\sum_{EXPMTL} \beta_i)/7 - \sum_{CONTROL} \beta_i/10 = 0$ in the SUR model is rejected, with F-statistic $= 12.44$ and Prob. $> F = 0.0005$, when the summation for the control plants excludes the one with a significant productivity increase.

Finally, we re-estimated the fixed-effects and SUR models for the experimental plants after including an independent variable reflecting the average productivity of the 10 control plants. The reporting change coefficient is -0.107 ($t = -5.443$) for this fixed-effects model. The hypothesis $\sum \beta_i = 0$ for the reporting change coefficients in the SUR model is also rejected with F-statistic $= 20.21$ and Prob. $> F = 0.0001$.

The estimated SUR model also indicates a significant decline in labor productivity in three control plants. We presented productivity data separately for each plant to its managers in order to elicit explanations for the behavior of productivity over time. For control plant 8, there was a negative "blip" in month 31 (*PRDTVT* $= 0.58$); it was explained to be a result of machine breakdowns and line adjustments. For control plant 10, there was one positive "blip" in month 1 (*PRDTVT* $= 1.47$); it was to be a result of an adjustment for a reporting error in the previous month (the month prior to our sample period) that could not be corrected for that month itself because the books had been closed. When we delete these two observations and re-estimate our model for these two plants, they no longer exhibit a statistically significant decline in productivity ($\hat{\beta} = -0.035$, $t = -1.067$, for

[11] Further, we tested the equality of coefficients across plants for the SUR models and could not reject equality, implying that pooling in fixed effects model is appropriate.

control plant 8; and $\hat{\beta} = -0.033$, $t = -1.405$ for control plant 10). For control plant 6, there is a decline during the second year of our sample, but little change in the third year, the year after the reporting change. This is evident also from the regression results when we include dummies for years 1 and 3 ($\hat{\beta}_{YEAR1} = 0.103$, $t = 1.908$; $\hat{\beta}_{YEAR3} = -0.035$, $t = -0.698$). This decline was described as the result of the disruption caused by continuing adjustments to the production process as Protech was considering the possibility of a change in its customer mix for this plant.[12]

4.7 MANAGERIAL SIGNIFICANCE

Although the reporting change has a statistically significant impact on labor productivity, its managerial significance depends on its monetary impact. We present below analysis based on estimates from the fixed effects model to evaluate the monetary impact of the decline in labor productivity. The coefficient of the reporting change variable in table 3 implies an 11.0% average reduction in normalized labor productivity as a result of the reporting change. Since shopfloor labor is 33.5% of total manufacturing costs, the decline in labor productivity implies a 3.7% (=0.110 ∗ 33.5%) increase in manufacturing costs. This increase is managerially significant in Protech's competitive industry.

We also estimate the increase in total labor hours required per month after the reporting change for each experimental plant. Multiplying this increase by the average wage rate for each plant provides an estimate of the total additional costs attributable to the decline in labor productivity. The estimated total annual loss due to the decline in labor productivity for the seven experimental plants is \$1,996,000; estimated savings from eliminating separate direct labor reporting were \$200,000. These estimated savings include the time of accounting clerks and production supervisors, and information systems resources no longer required, but they exclude the shopfloor labor time saved because the latter is already accounted for in the estimation of changes in shopfloor labor productivity. The estimated annual product cost savings because of fewer rejects is \$319,000, small relative to cost of the productivity decline. However, the long term impact of improvements in quality is difficult to quantify and, therefore, these numbers understate the true benefit from the reporting change.

Following a referee's suggestion, we provided a draft of this paper and presented its results to senior Protech managers.[13] Several managers stated

[12] We do not control for these explanations in our estimation models as we did not discover them in our initial inquiry and discussions with managers to identify potential explanatory factors; they emerged as explanations only after we provided our analysis of productivity data to managers.

[13] Interviews are useful in understanding managers' "beliefs" before they are presented with research results and their "rationalization" of results when they are asked to explain the results. However, readers should not interpret interview results as "facts" about actual operations. Managers' perceptions are at times inconsistent with facts gleaned from a careful analysis

that our results confirmed their observations. Production supervisors used to deal with low productivity workers by showing them their productivity performance reports; without the reports they found it harder to control workers. Some felt that a few workers were taking longer breaks and a few appeared to be working more slowly. Some managers observed that production supervisors and workers perceived less productivity pressure and demonstrated greater enthusiasm about quality improvements. The frequency of suggestions for process improvements from workers seemed to have increased in recent months. Senior managers also found the estimated 3.7% increase in manufacturing costs attributable to the decline in labor productivity to be substantial. Consequently, they appointed a new task force to examine whether and how direct labor variance reporting should be reintroduced to recoup some of the productivity losses while sustaining the improvements in quality. We were informed that Protech has decided to reinstate direct labor variance reporting.

5. *Concluding Remarks*

Using a field study approach, we investigated the productivity and quality impacts of eliminating direct labor variance reporting in manufacturing plants. We analyzed a panel data set containing 36 months of data from seven experimental plants that eliminated direct labor variance reporting and 11 control plants that did not. Our study supports the view that direct labor variance information is useful for monitoring and controlling manufacturing workers. Plants that stopped such reporting experienced an 11% decline in labor productivity, which was significantly greater than that for plants continuing the variance reporting.[14] These results are robust to alternative measures of total and partial labor productivity, different base periods for comparison with the period after the reporting change, and different estimation techniques.

Our results support the prediction that workers will reallocate efforts to other tasks as a result of the change in the information set available to evaluate them. At our research site, the shift in managers' focus resulting from the elimination of direct labor variance reporting, leads to a significant increase in product quality. The immediate benefit of cost savings due to a lower reject rate is only one-sixth of the cost increase due to lower labor productivity. However, long term benefits of quality improvements, such as increase in sales or brand name value, remain not quantified.

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of archived data. Managers' perceptions may be influenced by popular articles promoting fashionable ideas, and their "beliefs" may change when confronted with the task of explaining contrary evidence backed up by data.

[14] In this context, it is of interest to Banker, Potter, and Schroeder's [1993] finding that while plants employing just-in-time and quality improvement practices rely more on non-financial measures than plants that do not, there is no significant difference in their reliance on direct labor variance reports.

Since all 7 experimental plants in our study belong to a single firm, our results may not generalize to other firms that differ substantially from Protech. For instance, the impact of eliminating direct labor variance reporting may be very different in firms for which shopfloor labor costs account for much less than the 33.5% of total manufacturing costs reported by our seven experimental plants. Notwithstanding this limitation of a field study, a unique advantage of our research setting is that we can calibrate the productivity and quality impacts of eliminating direct labor variance reporting in the experimental plants against control plants from the same industry, under the same management and labor contracts, and at the same geographic location. Unlike the experimental plants, the control plants did not change their direct labor reporting systems, and they did not experience statistically significant productivity and quality changes.

APPENDIX A. RESEARCH SITE

Our research site, Protech, is a division of a manufacturer of control equipment. The 18 plants that comprise our study sample share a general manager but each has a different plant manager. All 18 plants are governed by the same management policies and labor contracts although they function as independent units. All are in SIC 3822, Automatic Controls for Regulating Residential and Commercial Environments and Appliances. Specifically, products manufactured at these 18 Protech plants include air-conditioned controls, appliance thermostats, electric heat controls, and humidity controls. Interviews with managers, personal observations and review of internal documents indicated that the technology and products at these plants were mature, and remained stable during the period of our study.

Shopfloor labor costs comprise on average 33.5% of the manufacturing costs for the seven experimental plants, and range from 24.2% to 41.5%. The fact that a significant component of total manufacturing costs, 33.5% for the seven experimental plants, is labor costs highlights the significance of direct labor variance reporting and its potential to impact manufacturing performance. About 80% of the shopfloor labor costs are direct labor costs identified with specific production jobs, and the remaining are indirect costs such as setup and materials handling. Manufacturing support activities (including production planning and control, stores, engineering, tools and custodial services) comprise an additional 23.7% of the manufacturing costs on average for the seven plants, and direct materials account for 41.5%. Capital and energy costs comprise 1.0% and 0.3% of the manufacturing cost respectively. The accounting system at the 11 control plants does not maintain a separate record of direct material costs by plant, but as at the seven experimental plants, the proportion of materials costs to conversion (shopfloor labor plus overhead) costs is about 40:60. Shopfloor labor comprises 41.6% of conversion costs, manufacturing support services comprise an additional 55.6%, and capital and energy costs together account for less than 3% of conversion costs on average at the 11 control plants.

The 11 control plants have relatively more fabrication activities and fewer assembly activities than the seven experimental plants. The control plants have only a few customers, including other units of Protech with whom they have long-term certified supplier-type relationships. Production at these plants is typically in large batches identified with specific customers. Consequently, the production scheduling and manufacturing resource planning (MRP) system at the control plants is different from that at the experimental plants. The material accounting system also is different because material is usually supplied by the customer or acquired and charged directly to the customer. Quality inspection policies are different as the control plants perform 100% inspection to assure "zero defects" to their long-term customers, while the experimental plants test only samples and defective devices are returned by customers.

All 18 plants had quality improvement programs in place for over 10 years and just-in-time (JIT) production systems in place for over 6 years prior to our sample period. Workers are encouraged to suggest quality improvements which usually implies lower labor productivity in the short run as workers experiment with alternative ways to manufacture. Daily yield and monthly customer returns data are posted on the shopfloor and aggregate monthly data are reported to plant managers and supervisors. Workers are given small rewards and public recognition for improvements in quality. Because Protech's manufacturing process is relatively labor intensive, improvements in labor productivity, along with process and product quality, are important for continued business success. Production supervisors are responsible for identifying and counseling less productive workers, who may be dismissed for continued poor performance. The most productive workers are recognized as "key players." Thus, tangible and intangible incentives are associated with both quality and productivity aspects of worker performance.

A.1 LABOR REPORTING SYSTEM

The labor payroll system at Protech is based on daily timecards punched by each worker that record the actual time spent at the plant. Workers are identified as either shopfloor workers or manufacturing support workers. Thus, information on total actual shopfloor labor hours is available from the payroll system.

Previously, a parallel reporting system tracked detailed direct labor data for individual production jobs. Shopfloor workers manually recorded time, job number, and quantity completed for direct production jobs, and time used for indirect production activities, on "labor tickets" when they completed each task during each shift. Production supervisors collected and reviewed all labor tickets at the end of each shift. A labor reporting system generated daily reports. Accounting clerks and production supervisors reviewed these reports, reconciled them with payroll data, and tracked down "missing" labor data. Accounting clerks posted the corrected data to individual production jobs. The system generated weekly reports of direct labor costs and variances individually by worker and by production job, including comparative data for the preceding six weeks. Plant managers and production supervisors received the reports and discussed them with individual workers when appropriate.

Based on the recommendation of a management task force, Protech's managers decided to eliminate the detailed reporting of direct labor information. This decision was implemented immediately at the seven experimental plants. The system was continued at the other 11 plants because it was integrated with their production scheduling and MRP systems. Managers at these plants expected detailed labor reporting to be eliminated when their MRP system software was updated.

The management task force estimated the annual cost to operate the direct labor reporting system and the timecard and payroll system to be \$500,000 and \$80,000, respectively.[15] Of the \$500,000 direct reporting cost, about \$300,000 was for shopfloor workers filling out daily labor tickets, about \$140,000 represented time spent by production supervisors and accounting clerks to check, track, and report the information and about \$60,000 represented computer costs. The costs of this system at the 11 control plants were about \$800,000 annually.

Our interviews and inspection of documents indicated that cost reduction was the primary motivation for eliminating the direct labor reporting system. Managers also expected the change to free up time for supervisors and workers to focus on quality improvements.

APPENDIX B. CONTROL VARIABLES

B.1 STRUCTURAL FACTORS

The plants at our research site used mature technologies to manufacture mature products for a stable customer base. Protech's chief engineer and senior plant managers informed us that there were no significant changes in technologies, production processes, and raw materials used at the 18 plants during the sample period. Personal observations and review of internal documents, including annual summaries of capital expenditures, confirmed these assertions. Further, our use of normalized measures eliminates cross-sectional variations prior to the reporting change. Therefore, we do not include separate variables for most structural factors. The exception is capacity utilization. Since plant capacity remained unchanged at all plants during the sample period, capacity utilization is reflected in production volume.

Volume of production (*VOLUME*) is measured as the number of units worked on during a month in a plant, normalized by the average for the first

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[15] All cost and production data presented here are multiplied by a constant to disguise competitively sensitive information.

24 months. Productivity increases with the volume of production to the extent costs are fixed.

B.2 EXECUTIONAL FACTORS

To control for executional factors, we proceeded as follows:

EQUIPMENT POLICY. Protech's chief engineer and plant managers indicated that equipment maintenance policies were similar across the 18 plants and did not change during our sample period. Plant records confirmed this assertion. Therefore, we do not include any variables to reflect equipment policy.

INVENTORY POLICY (WIP). Productivity growth is frequently attributed to the adoption of JIT inventory policy (Schoenberger [1982], Shingo [1988], Lieberman, Lau, and Williams [1990]). Since all Protech plants used JIT throughout the 36-month study period, we control for the effect of JIT on performance. Following Lieberman et al. [1990], who contend that the key feature of a JIT system is continual reduction in work-in-process (WIP) inventory levels, we use WIP inventory scaled by production volume to measure the extent of JIT implementation, and normalize it by the average for the first 24 months.

WORKFORCE POLICY. We developed a comprehensive list of compensation, incentives, recruitment, promotion, layoff and training practices based on a review of the relevant literature (Katz et al. [1989], Ichniowski et al. [1997], Kelley [1994], MacDuffie [1995], Banker et al. [1996]). We presented this list to plant managers and Protech's labor relations manager who confirmed that there were no systematic variations in these practices across the 18 plants, or during the sample period. Workers in all 18 plants belonged to the same union and a new contract was negotiated two years before the beginning of the sample period.

POLICIES AFFECTING CONFUSION IN OPERATIONS. Changes in workforce, absenteeism and disruptions in production schedule engender confusion in operations. We control for these executional factors as follows:

Overtime (OVTIME) is the normalized ratio of overtime hours to actual total labor hours worked in a month. Overtime workers are believed to be more prone to fatigue and stress than regular shift workers. Performance declines when a significant portion of total labor hours is overtime work (Hayes and Clark [1985]). However, support services and infrastructure costs do not increase proportionately during overtime work, and the productivity of these resources increases.

Turnover (ADDN). In a survey of 350 U.S. manufacturing facilities, Cooke [1989] found that labor turnover decreases productivity. At Protech, labor turnover is measured as the ratio of the number of new employees hired in a month to the total head count of employees at the end of the month. *ADDN* is this ratio normalized by the average for the first 24 months.

Positive and negative fluctuations in production volume (PFLUCT, NFLUCT). Changes in production rates disrupt operations and harm performance (Hayes and Clark [1985]). At Protech, plant managers made conscious, but sometimes unsuccessful, efforts to maintain uniform plant loads. We measured *positive fluctuations* (*PFLUCT*) as the normalized percent increase in production volume relative to the previous month's production if there is an increase, zero otherwise, and *negative fluctuations* (*NFLUCT*) as the normalized percent decrease in production volume relative to the previous month's production if there is a decrease, zero otherwise.

B.3 SEASONAL FACTORS

Production supervisors at Protech report labor productivity is lower in Summer (*QUARTER2*) and Fall (*QUARTER3*) compared to Winter (*QUARTER1*) and Spring (*QUARTER4*). They attribute this differential to outdoor activities that distract workers and require redeployments to fill in for absent workers. We account for possible seasonal differences with dummy variables for the last three quarters as detailed absenteeism data by month or quarter are not available.

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