Productivity Measurement and the Relationship between Plant Performance and JIT Intensity*

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Abstract

The management accounting and operations management literatures argue that the adoption of advanced manufacturing practices, such as just-in-time (JIT), necessitates complementary changes in a firm's management accounting and control systems. This study uses a sample of JIT and non-JIT plants operating in the Canadian automotive parts manufacturing industry to study the interaction among performance outcomes, intensity of JIT practices, and productivity measurement. This study provides evidence that productivity measurement mediates the relationship between performance outcomes and intensity of JIT practices. Specifically, both JIT and non-JIT plants that use a broader range of productivity measures are more efficient and profitable than other plants. Also, plants that employ industry-driven productivity measures are more profitable and efficient than plants that employ idiosyncratic productivity measures, especially if the former are more JIT-intensive than the latter. Furthermore, plants that employ quality productivity measures are less efficient and less profitable than those that do not, especially if they use more intensive JIT practices. The latter result is consistent with JIT-intensive plants overinvesting in quality. This study also finds that plants that invest more in buffer stock are less efficient and less profitable, especially if they use more intensive JIT practices. Despite the fact that plant profitability and efficiency are highly correlated, JIT-intensive plants are more profitable but less efficient than plants that are not JIT-intensive, after controlling for productivity measures, plant size, and buffer stock. This result suggests that despite wasting resources, JIT-intensive plants are still able to generate relatively higher profits than plants that are not JIT-intensive.

Keywords Just-in-time; Management accounting systems; Plant efficiency; Productivity measures

JEL Descriptors M41, M11, L62

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1. Introduction

Banker, Datar, and Rajan (1987) and Banker, Datar, and Kaplan (1989) decry the fact that productivity measurement has largely gone unnoticed by accounting scholars even though productivity improvement is a key objective of the corporate sector. Although empirical accounting research on nonfinancial performance measurement is now fairly common, accounting research on productivity measurement per se is still meager. This is somewhat surprising considering the voluminous number of economics and engineering studies dealing with productivity at the micro and macro levels.[1]

Productivity measures are essentially a subset of nonfinancial performance measures relating inputs to outputs. There are two types of productivity measures: partial productivity and total factor productivity. Partial productivity measures relate a given input to outputs, such as output per worker or energy use per unit of output. Total factor productivity measures the ratio of total outputs to total inputs including capital. The various outputs (inputs) are aggregated using average revenue (cost) shares. The goal of productivity measurement is to provide management with metrics that are useful for monitoring and improving productivity, by highlighting areas that would benefit from an increase (decrease) in outputs (inputs).

Increased global competition over the past two decades has forced U.S. manufacturers to implement new manufacturing strategies in an attempt to increase productivity.[2] One such strategy, lean production, incorporates a wide variety of management practices, including just-in-time (JIT), total quality management (TQM), cellular manufacturing, and integrated supplier management systems. It is believed that lean production methods ultimately yield a high-quality system, with high customer satisfaction and almost no waste (Shah and Ward 2003).

This study analyzes the interaction among performance outcomes, investment in JIT practices, and productivity measurement at the plant level.[3] The focus is on nonfinancial productivity measures **[AU: CAR style prefers limited use of italic for emphasis. Much of original emphasis has been deleted]** in Canadian automotive parts manufacturing. Two performance outcomes are at issue: technical efficiency (measured by a stochastic frontier production function) and accounting profits. The emphasis that the JIT philosophy places on waste management and productivity improvement (Yasin, Small, and Wafa 1997) makes the JIT environment ideal for investigating the mediating effect of productivity measurement on organizational efficiency and profitability. The Canadian automotive parts manufacturing industry is particularly useful to study because it is characterized by the coexistence of both JIT and non-JIT plants operating within the same geographical region. The focus on productivity measures per se is motivated both by the paucity of empirical accounting research on productivity measurement, despite the fact

that productivity is a key corporate objective, and by the potential importance of productivity measurement for monitoring operations and for identifying opportunities to improve operations in the automotive parts manufacturing industry.[4] It is also facilitated by the willingness of plant managers in the Canadian automotive parts industry to provide proprietary productivity data.[5]

The paper is organized as follows. Section 2 surveys the extant literature on nonfinancial performance measurement and performance outcomes in a JIT/TQM environment and develops the hypotheses to be tested. Section 3 provides further theoretical support for the hypotheses developed. In section 4 we describe the sample data and in section 5, estimate the stochastic production frontier and provide summary statistics. Section 6 tests the hypotheses. Section 7 concludes. Efficiency measurement through a stochastic frontier production function is described briefly in an appendix.

2. Literature review and hypotheses development

Despite the widely held assumption that the adoption of JIT/TQM increases profits by reducing waste and inefficiencies in the production process, the empirical evidence is decidedly mixed (Huson and Nanda 1995; Ittner and Larcker 1995, 1998, 2001; Balakrishnan, Linsmeier, and Venkatachalan 1996; Sim and Killough 1998; Callen, Fader, and Krinsky 2000; Callen, Morel, and Fader 2003; Mia 2000; Cua, McKone, and Schroeder 2001; Fullerton and McWatters 2001, 2003; Kinney and Wempe 2002; Fullerton, McWatters, and Fawson 2003; and Taylor and Wright 2003). Of the three primary potential explanations for these inconclusive results, the complementary relationship between the firm's technology and its management accounting system (MAS) is central to this study.[6] The other two major potential explanations — namely, the long-run nature of the JIT implementation process and the nature of the data used to study the relationship between JIT/TQM and profitability — also inform this study.

Performance consequences of JIT/TQM and the management accounting system

Milgrom and Roberts (1990, 1995) argue that modern manufacturing practices are mutually complementary and that their adoption is a profit-maximizing response on the part of firms. In a similar vein, many studies have suggested that the benefits to be derived from advanced manufacturing implementation, including JIT/TQM, are dependent on complementary changes in the firm's internal control systems, including its MAS (Bennet and Cooper 1984; Ansari and Modarress 1986; Barney 1986; Green, Amenkhienan, and Johnson 1991; Hendricks 1994; and Milgrom and Roberts 1995). If the MAS fails to change adequately to reflect the new technology, the performance consequences of JIT/TQM may well be attenuated, leading to inconclusive empirical results.

The principal change to the internal MAS promoted by the literature on advanced manufacturing is the use of comprehensive nonfinancial performance measures to supplement or, perhaps, even to supplant traditional financial performance measures.[7] Traditional financial performance measures, such as cost vari-

ances, it is argued, are only indirectly related to the underlying activities of the plant manufacturing process and are weak indicators of plant operational performance and productivity (Banker et al. 1987, 1989). Traditional measures tend to focus management attention on short-term objectives and are obstacles to effective implementation of the company's strategic goals (Kaplan 1983; Johnson and Kaplan 1989; Henricks 1994; Kaplan and Norton 1996; Ittner and Larcker 1998). For example, focusing on the material price variance may result in buying less expensive material whose quality is inconsistent with JIT requirements. By contrast, nonfinancial performance measures can be constructed that directly relate to the performance of the production and marketing activities that management wants to improve. Said, HassabElnaby, and Wier (forthcoming), **[AU: update available?]** among others, maintain that nonfinancial performance measures also have strategic value in communicating strategic intent to employees and in motivating performance toward establishing strategic goals.

These arguments are especially relevant to the JIT environment. JIT plant operations are inherently riskier than conventional plants because of their relatively limited holdings of work in process and finished goods buffer stocks. To minimize the risk of stock-outs, JIT necessitates continuous oversight of all aspects of the production and distribution processes to ensure process and product quality. Process/product quality ensures that the components/goods will be there when the plant is producing to demand without the need for excessive work in process and finished goods inventories. Thus, JIT plants are more likely than conventional plants to benefit from a wide range of nonfinancial performance measures (see Mia 2000; Ittner and Larcker 1998, 2001; Kaplan and Atkinson 1989, 421–5; Hilton 2001, 452–6; Upton 1998).

The empirical literature supports the argument that there is a positive relationship between the extent of advanced technology practices adopted and the range of nonfinancial performance measures used. Numerous empirical studies show that firms that use more advanced production processes make greater use of nonfinancial measures and reward systems (see Patell 1987; Banker, Potter, and Schroeder 1993a, b; Abernethy and Lillis 1995; Ittner and Larcker 1995, 1998; Durden, Hassel, and Upton 1999; Jazayeri and Hopper 1999). Regarding JIT/TQM environments, Daniel and Reitsperger (1991) show that managers of Japanese firms — who are also more likely to have adopted JIT/TQM — are more likely to receive feedback about inventories and production flexibility, with greater frequency, than their U.S. counterparts. Banker, Potter, and Schroeder (1993a) indicate that the availability and use of productivity measures are positively associated with the implementation of JIT/TQM. Banker, Potter, and Schroeder (1993b) observe positive correlations between the provision of manufacturing performance measures to line personnel and implementation of JIT, TQM, and teamwork practices. In addition, worker morale is found to be positively related to these manufacturing practices and to the reporting of performance information. Ittner and Larcker (1995) find that TQM practices are associated with greater use of nontraditional information and reward systems that depend on the specific TQM practice. Perera, Harrison, and Poole (1997) find that the use of performance measures increases with the level of

advanced manufacturing practices and technologies. Fullerton and McWatters (2002) show that firms implementing a higher degree of JIT are (1) more likely to use nontraditional performance measures and (2) more likely to tie compensation rewards to nonfinancial measures. Fullerton and McWatters (2002, 2003) find that "bottom-up" performance measures are significantly related to the degree of JIT implementation and that the frequencies of measuring and reporting quality and productivity results to all levels of employees are also significantly related to the degree of JIT implementation.

These studies lead to our first set of hypotheses expressed in the alternative form:

HYPOTHESIS 1(a). *JIT plants employ a broader range of productivity performance measures than do non-JIT plants.*

HYPOTHESIS 1(b). *JIT plants that have implemented a higher degree of JIT practices employ a broader range of productivity performance measures.*

Because JIT plants and conventional non-JIT plants use different production technologies, they are likely to differ not only with respect to the range of productivity measures employed, but also with respect to the types of measures employed. Specifically, to provide effective control in a JIT/TQM milieu, the MAS should direct the organization to eliminate unnecessary investment in work in process and finished goods buffer stocks. Indeed, perhaps the most consistent benefit of JIT adoption found in many empirical studies is the reduction in inventory levels (or increase in inventory turns) (Celley, Clegg, Smith, and Vonderembse 1986; Im and Lee 1989; Gilbert 1990; Crawford and Cox 1990; Billesbach 1991; Billesbach and Hayden 1994; Norris, Swanson, and Chu 1994; Huson and Nanda 1995; Balakrishnan et al. 1996; Callen et al. 2000; Fullerton and McWatters 2001). In addition, given the potential risk of stock-outs on increasing production costs and reducing customer satisfaction, it is commonly accepted that process and product quality are a sine qua non for efficient JIT production. Daniel and Reitsperger (1991) find process quality metrics such as setup times, scrap, and downtime are reported more frequently to managers who support zero-defect strategies than to managers who support more traditional strategies. Fullerton and McWatters (2002) find a significantly positive relationship between the extent of JIT practices and the frequency of measuring and reporting quality results to supervisors and managers. These empirical findings suggest the following hypotheses:

HYPOTHESIS 2(a). *JIT plants make greater use of inventory and quality-related productivity measures than do non-JIT plants.*

HYPOTHESIS 2(b). *JIT plants that have implemented a higher degree of JIT practices make greater use of inventory and quality-related productivity measures.*

Despite arguments to the effect that advanced manufacturing technologies, including JIT/TQM, require a complementary MAS to ensure profit-maximizing outcomes, the empirical evidence linking nonfinancial performance measurement and performance outcomes is mixed. In a field study of a JIT division of a manufacturing firm, Young and Selto (1993) find no correlation between performance across direct labor work groups based on nonfinancial performance measures and performance ratings. Sim and Killough (1998) find no customer performance and quality performance benefits from the provision of quality and customer-related performance measures in a JIT/TQM environment, although such benefits accrue from the provision of performance goals and performance contingent plans. Ittner and Larcker (1995) show an inverse relationship between performance and the intensity of TQM practices and nontraditional information and reward systems. Abernethy and Lillis (1995) find no association between the performance of firms that adopt a flexibility strategy and the use of efficiency measures. Contrariwise, they find a positive relationship between nonflexibility-oriented firms and the use of efficiency measures. Perera et al. (1997) find that increasing levels of advanced manufacturing practices and technologies are not associated with increased performance. Durden, Hassel, and Upton (1999) find evidence suggesting that JIT manufacturing companies that have made some degree of modification to their costing demonstrate higher performance than JIT companies that have not made changes. Their results also suggest that greater use of nonfinancial performance indicators is associated with higher performance irrespective of the production management system adopted. Fullerton and McWatters (2003) show that adoption of JIT/TQM practices, coupled with complementary use of nonfinancial performance tools, such as benchmarking and tracking manufacturing efficiency, contribute to higher financial performance.

This literature leads to the following set of hypotheses regarding the relationships between plant efficiency, plant profitability, and productivity measures in a JIT environment:

HYPOTHESIS 3(a). *Plants employing a broader range of productivity measures are more efficient in resource use and also more profitable than plants employing a narrower range of productivity measures, after controlling for plant size, the level of buffer stocks, and the degree of implementation of JIT practices.*

HYPOTHESIS 3(b). *Plants that have implemented a higher degree of JIT practices employ a range of productivity measure that is more highly correlated with plant efficiency and profitability.*

HYPOTHESIS 3(c). *Plants that have implemented a higher degree of JIT practices are more efficient and more profitable, after controlling for plant productivity measures, plant size, and the level of buffer stocks.*

3. Hypotheses development: The economic arguments

The hypotheses developed in the prior section are based primarily on the empirical findings of the extant literature. This section provides a set of complementary theoretical arguments to help bolster the logical underpinnings of these hypotheses whenever possible or, alternatively, if this is not possible, to show where their weaknesses lie.

Hypotheses 1(a) and 1(b) can be rationalized as follows. Performance measurement is costly. Each additional productivity measure that a plant adopts requires more data collection and analysis on an ongoing basis, which, in turn, is likely to require additional labor resources and/or monitoring equipment. Assume that the marginal cost function of an additional productivity measure is identical for both JIT and non-JIT plants. In contrast, the marginal return function of an additional productivity measure is likely to be greater for JIT plants than for non-JIT plants. As pointed out above, a JIT plant is operationally more risky than a non-JIT plant because of potential stock-outs. Thus, the marginal return from monitoring plant operations is potentially far greater for JIT plants than for non-JIT plants. Because the marginal cost of an additional productivity measure is independent of the technology and the marginal return of an additional productivity measure is greater for JIT plants, it follows that JIT plants use a broader range of productivity measures than non-JIT plants. This is illustrated in Figure 1. MR_{JIT} ($MR_{non\text{-}JIT}$) is the marginal return of an additional productivity measure for JIT (non-JIT) plants. MR_{JIT} is greater than $MR_{non\text{-}JIT}$ for all levels of productivity measures. MC is the marginal cost of an additional productivity measure. Q_{JIT}, the optimal number of productivity measures for JIT plants, is greater than $Q_{non\text{-}JIT}$, the optimal number of productivity measures for non-JIT plants.

[CATCH — figure 1 near here]

Because JIT plants and conventional non-JIT plants use different production technologies, they are likely to differ with respect to the types of measures used as well as the range of productivity measures employed. In particular, JIT plants focus on minimizing inventories and maximizing quality. Minimizing inventory is, of course, the essence of the JIT philosophy. Moreover, in the absence of buffer stocks, maintaining the quality of both inputs and outputs is crucial because there is only limited buffer stocks from which to draw down inventories if component/product quality fails. These considerations imply that the marginal returns to JIT plants from using inventory and quality-related productivity measures are far greater than for non-JIT plants. Assuming, once again, that the marginal cost of an additional productivity measure is independent of the technology gives rise to Hypotheses 2(a) and 2(b).

JIT plants should use a broader range of productivity measures than non-JIT plants in equilibrium, as illustrated in Figure 1. Nevertheless, assuming that all plants operate optimally, there should be no discernable relationship between plant efficiency, or profitability, and the range and types of productivity measures adopted by each plant after controlling for the level of buffer stock and (JIT versus

non-JIT) technology (Ittner and Larcker 2001). However, this argument assumes that all plants operate optimally. Allowing for operating inefficiency, it is not unreasonable to suppose that plants that operate relatively inefficiently (and, hence, unprofitably) are likely to have adopted a suboptimal range of nonfinancial productivity measures. Furthermore, because the marginal return of an additional productivity measure is probably difficult to quantify, especially by comparison to its marginal cost, it is possible to further maintain that the marginal return of an additional productivity measure is undervalued by the management of inefficient plants.[8] If this argument is correct, it follows that the suboptimal plant will employ fewer productivity measures than the optimum. This is illustrated in Figure 2. MR is the true marginal return of an additional measure, and MR_{under} is the undervalued marginal return. Q_{opt} is the optimal level of productivity measures, and Q_{under} is the suboptimal level of productivity measures. This argument rationalizes Hypothesis 3(a).

[CATCH — figure 2 near here]

If monitoring operations is relatively less beneficial for non-JIT plants, as argued above, any variability in the range of productivity measures is less likely to have performance consequences and, therefore, less likely to be correlated with variability in performance outcomes for non-JIT plants. In contrast, any variability in the productivity measures chosen by JIT plants is likely to be more highly correlated with variability in efficiency, or profitability, than would be the case for non-JIT plants. This argument leads to Hypothesis 3(b).

In what follows, we test the hypotheses on a data base of 61 JIT and non-JIT manufacturing plants operating in the Canadian automotive parts manufacturing industry. Callen, Fader, and Krinsky (2000) use this data base to compare the cost and profit structures of JIT and non-JIT plants without reference to productivity performance measurement, plant efficiency, or the productivity performance data. In contrast, our present analysis focuses on the specific productivity performance measures employed by these plants and their relationship to plant profitability and plant efficiency.

4. The sample

The mixed results found in the literature regarding the relationship between JIT/TQM adoption and profitability may also be due to the nature of the data employed. The sample data for most of the studies referenced earlier are at the firm-level. But JIT is a plant concept, not a firm concept. A given firm may operate both JIT and non-JIT plants simultaneously.[9] This aggregation bias may be driving the inconclusive results. Also, because operational data are almost always proprietary, studies of advanced manufacturing entities are based primarily on self-reported and aggregated "soft" survey data. Performance consequences in these surveys are based on questions such as: "JIT adoption has reduced plant work in process inventory in your plant from 0–20 percent, 21–40 percent, etc.? Are inventory turns an important measure of efficiency in your plant?" Performance consequences are often "perceived" rather than actual. As a result of the subjective and self-reporting

nature of the questions and the survey instrument format, which tends to elicit ranges rather than specific numbers, the data obtained are far less reliable and more aggregated than "hard" data. In addition, the sample data of many studies come from very disparate industries. On the one hand, this allows for a potentially more meaningful generalization of the results; on the other hand, controlling adequately for correlated omitted variables (such as industry competitiveness and organizational structure) is crucial if the results are to have any meaning.

Our data set mitigates these deficiencies. We attenuate the potential multiplant aggregation bias by using plant-level data. Although some of the data in this study are "soft" survey data, most are "hard" quantitative data, such as plant-level inputs, outputs, profits, and the types of productivity measures used. Because all sample plants are in one industry operating in the same geographic region, the problem of correlated omitted variables is mitigated (but not eliminated) relative to multi-industry studies.

A description of the sample follows. Initially, 87 plants in the automotive parts manufacturing industry in southern Ontario, Canada, between Windsor and Oshawa, were contacted in early 1991 to participate. This industry was chosen because it contains a mix of JIT and conventional non-JIT plants operating simultaneously in the same geographical area. Of these 87 plants, 18 declined to participate because they "did not have time" or "were not interested in participating", 6 declined to participate because they were "reorganizing and restructuring", and 2 plants never completed the survey instrument. The final sample comprised 61 plants.

The automotive parts manufacturing plants in this study produce a variety of parts, including plastic blow-molded components, stampings and welded assemblies, filters, electroplating, heat-treating tubing, tires, glass, molded foam, shock absorbers, and noise control products. Because the sample plants are situated in the same geographic location, the noise induced by cross-sectional differences in input prices and freight charges is mitigated. Plants are also required to have a minimal size of at least 50 employees. All plants are autonomous profit centers with pricing determined by market conditions. These plants are controlled almost exclusively by private firms, so market data are not available. Of the 61 plants, 56 belong to totally different firms. Of the remaining 5 plants, 3 plants belong to one firm and 2 plants belong to another firm.[10]

Two sets of data are collected for each plant: production-related survey data collected during the 1991 calendar year and financial data for the year 1990, denominated in Canadian dollars. The production survey data include plant production practices and various JIT/TQM characteristics (see Table 1) adopted by each plant. These data are measured primarily on the basis of five-point Likert scales. The financial data set comprises "hard" quantitative data and contains the information mandated by the Canadian government in its annual Census of Manufacturing. The data are obtained from each plant because they are not available from government sources on a disaggregated basis. In addition, the Census of Manufacturing also mandates data on the plant's in-house productivity measures. These data are described further below.

Plant (production) managers are asked in the survey instrument to classify their plant as JIT or non-JIT based on a narrow definition of JIT. This narrow definition emphasizes the stockless production aspect of JIT and defines JIT as "a system of manufacturing in which materials, parts and components are produced and delivered just before they are needed … . The goal of JIT production is to come as close as possible to the concept of ideal — or zero inventory — production." Plants that are classified by their plant managers as non-JIT on the basis of this narrow definition are deemed to be non-JIT.

Self-selection for classifying the JIT plants could be problematic if plants did not define JIT with some degree of consistency. Plants classified by their plant managers as JIT on the basis of the narrow definition *and* that had adopted JIT for at least one full year are further tested for the extent of JIT use, utilizing the JIT/TQM data from the production survey. The one-year restriction reflects the lengthy implementation process of JIT adoption. The production survey section identifies 17 characteristics designed to capture the extent of JIT/TQM implementation. These 17 characteristics and the selection procedure are rooted in the findings of Flynn et al. 1995 indicating that JIT techniques interact with and are difficult to distinguish from common infrastructure and TQM practices. This simply reflects the fact that while TQM plants need not be JIT, JIT plants necessarily place great emphasis on quality and quality improvement (Sim 2001). In the absence of quality, JIT plants would soon find themselves having to shut down or increase inventories in order to continue production. Because there is no single accepted set of measures in the literature that defines JIT, the 17 characteristics were culled from conversations with plant managers in the automotive parts industry and from the extant JIT/TQM literature, including Cheng and Podolsky 1983; Im and Lee 1989; Cheng 1990; White and Ruch 1990; Billesbach 1991; Ahmed, Runc, and Montagno 1991; and Mehra and Inman 1992. It is worth noting that of the 10 JIT/TQM practices employed in a recently published study by Fullerton et al. 2003, 9 are included in our list.[11]

Participants are asked to indicate the extent of plant usage of each of the JIT/TQM characteristics using a five-point Likert scale where 5 = always used and 1 = never used. A sum of 85 indicates that the plant uses all 17 techniques all of the time. A sum of 17 indicates that the plant never uses any of the listed JIT/TQM techniques. A plant is classified as JIT for purposes of this study if the plant manager classifies the plant as JIT on the basis of the narrow JIT definition *and* if both of the following two criteria are also satisfied: (1) a sum of 51 or greater is scored on the survey indicating that, on average, the plant uses all JIT techniques half the time (a score of 3 per technique), and (2) the plant uses two-thirds of the techniques at least half of the time. These criteria help to ensure — but do not guarantee — that JIT is both broadly applied and intensively used by each of the sample JIT plants.

Of the 61 survey responses from the automotive parts manufacturing plants, 19 plants declare themselves to be non-JIT. Of the remaining 42 plants, 3 are reclassified as non-JIT on the basis of the above criteria, resulting in a final sample of 39 JIT and 22 non-JIT automotive parts manufacturing plants.[12] Table 1 summa-

rizes the 17 JIT/TQM characteristics and a variable measuring experience with JIT for the sample of 39 JIT plants.

[CATCH — table 1 near here]

JIT plants are not entirely homogeneous in their adoption of JIT techniques. Some plants employ a more comprehensive set of JIT techniques. Other plants adopt fewer JIT techniques but use them more intensively. To accommodate potential heterogeneity among JIT plants, an index of "JITness" — hereinafter called the JIT concentration index — is developed to capture plant differences in the breadth, intensity, and length of experience with JIT practices. Length of experience with JIT is important in characterizing JIT plants. Callen et al. (2000) and Fullerton et al. (2003) find that the impact of JIT experience on performance outcomes is significantly affected by experience with JIT.

The JIT technology index for each JIT plant is computed from a principal components analysis of 18 factors, the 17 JIT/TQM characteristics, and years of experience with JIT.[13] The principal components approach is necessary because of collinearity among some of the JIT/TQM characteristics and limited degrees of freedom. Principal components analysis of these data yields only one factor with an eigenvalue greater than 1. This factor solution preserves 84 percent of the total variation in the data. Unfortunately, the survey instrument failed to require non-JIT plants to complete the section of the questionnaire dealing with the JIT/TQM characteristics. Therefore, all non-JIT plants are assumed to have a minimum JIT technology index value of 17.[14]

As part of the federal government's annual Census of Manufacturing survey, all Canadian manufacturing plants are asked to provide information regarding their in-house plant productivity measures. Respondents are provided with four specifically defined productivity performance measures and are asked to indicate which of the measures are employed in their plant. The four measures listed in the survey are

1. total productivity = total output/total input;
2. labor productivity = total output/labor;
3. return on investment = net income/total investment;[15]
4. quality = number of acceptable units/(total processing cost + total correction cost).

In addition, a catch-all "other" category elicits the in-house plant productivity performance measures other than the four specific measures. In a follow-up question, respondents are asked to indicate how the "other" productivity measures are calculated. The list of other plant productivity measures proved to be quite heterogeneous, including such measures as products shipped per person-machine, machine idle time per total machine time, and rejected parts per parts inspected. Except for a rate measure — defined as output per hour — used by about 23 (3)

percent of non-JIT (JIT) plants, the remaining productivity measures are too heterogeneous to categorize separately.

5. Estimation of the stochastic production frontier

Plant-level efficiency in this study is measured by a stochastic frontier approach. See the appendix for a brief explanation of this methodology. Because the production technology of JIT plants likely differs to some extent from that of conventional non-JIT plants, even if both plant types are in the same industry, the functional form of the assumed stochastic production function frontier must be sufficiently general that it is able to incorporate both technology types.

The production function is assumed to be Cobb-Douglas. Although it would be preferable from a theoretical point of view to assume a more general production function, such as the translog, and then test for the Cobb-Douglas specification, the number of inputs (4) and our sample size (61) do not permit efficient estimation of a more general functional form.[16] Specifically, the stochastic frontier production function in this study is assumed to take on the form:[17] **[AU: verify that the function exp takes curly braces, not round brackets]**

$$Y_i = \Pi_j A X_{ij}^{(\alpha j + JIT.bj)} \exp\{\varepsilon_i\} \qquad (1),$$

where Y_i denotes the output of plant i, X_{ij} denotes input j, $\varepsilon_i = v_i - u_i$, v_i is a symmetric error term, u_i **[AU: ε_i? if not, please clarify]** is a one-sided error term, and *JIT* denotes the JIT technology index. This specification assumes that both JIT and non-JIT plants are Cobb-Douglas. However, the parameters of the production function for JIT plants are permitted to reflect JIT concentration *and* to be different from those of non-JIT plants. Dropping the i subscript for simplicity and taking logs of (1) yields the function to be estimated:

$$\ln(Y) = \alpha_0 + \Sigma_j \alpha_j \ln(X_j) + \Sigma_j \beta_j JIT \ln(X_j) + \varepsilon \qquad (2).$$

If the β_j parameters are identically zero, then the JIT plant production technology is identical to that of conventional non-JIT plants.

In order to estimate the stochastic production frontier, industry inputs and outputs need to be defined. We define output as the retail value of goods produced during 1990. We specify four inputs: labor,[18] energy,[19] materials,[20] and capital.[21]

Table 2 presents two models estimated by maximum likelihood.[22] The first unrestricted model is the estimated stochastic production frontier, (2), assuming that the v_i are normally distributed and that the u_i **[AU: ε_i?]** are distributed truncated-normal. Both error terms are assumed to be homoscedastic.[23] The second model is the estimated production frontier under the restriction that the β_j are identically zero, implying that JIT plant technology is not significantly different from non-JIT plant technology.

On the basis of a likelihood ratio test, we are able to reject the restricted model at the 1 percent significance level.[24] This implies that the production func-

tion coefficients of JIT plants are significantly different from the production function coefficients of conventional non-JIT plants. Therefore, in what follows, we use the more general unrestricted stochastic frontier to measure plant efficiency.

The test statistic γ in Table 2 is significantly different from zero (but not significantly different from 1) on the basis of a *t*-test (two-tailed, $t = 32.95$), indicating that the one-sided error term is necessary. A log likelihood ratio test ($\chi^2(2) = 6.836$) of the one-sided error term is also significant. The point estimate $\gamma = 1$ implies that the stochastic error in the production function is due primarily to production inefficiency.

Table 2 shows that the α coefficients **[AU: verify alpha; character on manuscript was not alpha]** are significant at conventional levels except for the capital input (and the intercept).[25] All β coefficients **[AU: verify beta; character on manuscript was not beta]** except for fuel are significant. The fuel and materials coefficients of the non-JIT plants are greater than those of the JIT plants, whereas the capital and labor coefficients of the JIT plants are greater than those of the non-JIT plants. The sum of the point estimates of the production function coefficients is 1.04 for both non-JIT plants and JIT plants (at the median value of JIT concentration), suggesting that the automotive parts manufacturing industry exhibits constant returns to scale irrespective of the technology.

[CATCH — table 2 near here]

Calculations in the appendix show that mean plant efficiency is 85 percent and that, on average, sample plants in the automotive parts manufacturing industry operate at significantly less than 100 percent efficiency at the 95 percent confidence level.[26] Table 3 provides summary univariate statistics for the plant efficiency scores, derived from the estimated unrestricted stochastic production frontier of Table 2. The distributions of the efficiency scores — categorized by whether the plant is JIT or non-JIT — suggest that non-JIT plants are significantly more efficient than JIT plants. This is supported by a *t*-test and a Wilcoxon signed rank test. The estimated correlations between plant efficiency and the JIT technology index (Pearson = −0.095, Spearman = −0.042) are not significantly different from zero. In contrast, Table 3 shows that plant efficiency and plant profitability are highly positively correlated (Pearson = 0.691, Spearman = 0.665). Thus, as expected, plants that are more efficient are also more profitable. Because these test statistics are univariate, the results are only suggestive.[27] More conclusive results are offered in the multiple regression analyses in Tables 5, 6, and 7 below.

[CATCH — table 3 near here]

6. Testing the hypotheses

Univariate tests of Hypotheses 1 and 2

We theorize (Hypothesis 1(a)) that JIT plants are more likely to use a broader set of in-house productivity measures than non-JIT plants. This hypothesis is strongly supported by Table 4, which shows summary statistics of in-house productivity measures categorized by technology. JIT plants use almost twice as many pro-

ductivity measures as non-JIT plants. Specifically, the mean (median) number of productivity measures (*TOTAL*) used by JIT plants is 5.9 (5) as compared with 3.2 (2) for non-JIT plants, and these differences are highly significant.

[CATCH — table 4 near here]

We also postulate (Hypothesis 1(b)) that JIT plants that implement a higher degree of JIT concentration employ more productivity measures. This hypothesis is corroborated by the significant Pearson (Spearman) correlation between the JIT concentration index for JIT plants and *TOTAL* of 0.426 (0.562).

One could argue that the number of productivity measures employed by each plant is a potentially distorted measure of the range of productivity measures, because productivity measures for a given plant can be similar in nature. For example, sales per employee and value of goods shipped per employee are likely to be highly correlated and are not really distinct productivity measures. To overcome this potential bias, similar productivity measures are aggregated yielding a new variable *DISTINCT* that measures the number of distinct productivity measures used by each plant. The empirical results using *DISTINCT* are similar to those using *TOTAL*, strengthening our hypothesis that "JITness" and number of productivity measures are related.

We theorize (Hypothesis 2(a)) that JIT plants are likely to make greater use of inventory- and quality-related productivity measures by comparison to non-JIT plants. This hypothesis is also supported by the data. The significant Pearson (Spearman) correlation between the JIT concentration index for JIT plants and the number of quality- and inventory-related productivity measures is 0.360 (0.449). In addition, Table 4 shows that JIT plants on average are significantly more likely than non-JIT plants to use *INVENTORY CONTROL* (1.03 versus 0.36) and *QUALITY* (0.97 versus 0.23) productivity measures.[28]

Table 4 indicates that JIT plants are significantly more likely than non-JIT plants to use *TFP* and *ROI* in-house productivity measures. Furthermore, all but one of the plants employ a labor productivity (*LP*) measure. This may seem somewhat surprising considering the biased nature of labor productivity by comparison to total factor productivity.[29] Because automotive parts manufacturing plants are highly unionized, the politics of a unionized shop may dictate the extensive use of a labor productivity measure in this industry whether the plant is JIT or non-JIT. Alternatively, the labor productivity measure may be easier for management and line workers to relate to and understand.[30]

Multivariate test of Hypotheses 3(a), 3(b), and 3(c)

To test this set of hypotheses, we estimate two sets of three regressions each, alternatively using plant efficiency and plant profitability as the dependent variable. The independent variables are the JIT concentration index (*JIT*), the total number of in-house productivity measures employed by the plant (*TOTAL*), the level of buffer stock (*BUFFER*) measured as the plant's average annual inventory value — including fuel, work in process, and finished goods inventories — normalized by the value of production at retail, and, in the case of the efficiency regressions, plant

size (*SIZE*) measured by the log of production (measured at retail prices).[31] We then extend these regressions to include the three latter variables interacted with the JIT index in case the slope coefficients depend on the technology. To mitigate multicollinearity concerns, especially in the regressions with interaction terms, all regressors are demeaned (Aiken and West 1991).[32]

Because plants with more investment in buffer stock are likely to be less efficient and less profitable than their cohorts, we expect a negative buffer stock coefficient. We make no assumptions regarding the size control variable.

Efficiency regressions

The efficiency regression results are presented in columns (1) to (3) of Table 5. The column (1) ordinary least squares (OLS) regression is consistent with Hypothesis 3(a).[33] Specifically, the *TOTAL* coefficient estimate is positive and statistically significant, although each additional productivity measure increases plant efficiency by an economically modest 1.5 percent. The estimated coefficient for *JIT* is significantly negative, implying that plants with more JIT concentration are less efficient, thus rejecting Hypothesis 3(c). Although the buffer stock coefficient is negative as expected, it is insignificant. The size coefficient is also insignificant.[34]

[CATCH — table 5 near here]

OLS assumes that the regressors are contemporaneously uncorrelated with the error term. If the adoption of JIT is endogenously determined, which would be the case if more efficient and profitable firms choose to adopt the JIT technology, then the JIT index may be contemporaneously correlated with the error term. To account for the potential endogeneity of JIT, we estimate the efficiency relationship by two-stage least squares (2SLS). Beginning-of-period work in process and finished goods inventories (normalized by sales) are the instrumental variables. If JIT plants hold less inventories (per dollar of sales) than non-JIT plants, these inventories should be negatively correlated with the JIT concentration index regressor.[35] In fact, the correlations of the JIT index with beginning-of-period work in process and finished goods inventories are significantly negative, -0.318 ($p = 0.013$, two-tailed) and -0.491 ($p < 0.000$, two-tailed), respectively. Also, because these are last period ending inventories, they should be uncorrelated with the current error term.

Column (2) of Table 5 shows the efficiency regression estimated by two-stage least squares. The results are remarkably similar to the OLS results. Endogeneity of the JIT decision is rejected at the two-tailed 5 percent significance level using a standard Hausman specification test.[36]

Column (3) of Table 5 shows the OLS efficiency regression where the independent variables interact with the JIT concentration index in order to examine the impact of JIT technology on the slope coefficients of the independent variables.[37] The insignificant interaction coefficient for *JIT*TOTAL* suggests that the relationship between efficiency and (the number of) productivity measures is independent of the plant technology, thereby rejecting Hypothesis 3(b).

Profitability regressions

The plant profitability regression results are given in columns (4) to (6) of Table 5, where profitability is measured by earnings before taxes normalized by the value of production at retail (*PROFIT*).

The column (4) OLS profitability regression is far more significant ($F = 13.01$ versus 2.66) than the equivalent efficiency regression in column (1). The coefficient for *TOTAL* is positive and significant, and consistent with Hypothesis 3(a), implying that plant profitability is an increasing function of the number of productivity measures employed by the plant. Consistent with Hypothesis 3(c), the JIT concentration index is also positive and significant, implying that plants that implemented more JIT practices are more profitable. The buffer stock coefficient is insignificantly negative.

Column (5) of Table 5 provides 2SLS estimates of the profitability regression. The results are quite similar to the OLS regression, although endogeneity of the JIT decision could not be rejected at the 5 percent level on the basis of a standard Hausman specification test.[38]

Column (6) of Table 5 shows the OLS profitability regression where the independent variables are also interacted with the JIT concentration index. The results for the noninteracted terms are similar to the previous two regressions except that the buffer stock variable is now significant and negative. Similar to the efficiency regression, the *JIT*TOTAL* interaction term is not significant, thereby rejecting Hypothesis 3(b).

In summary, Table 5 indicates that plants that use more productivity measures are both more efficient and more profitable, as posited by Hypothesis 3(a). Hypothesis 3(c) is only partially confirmed. The more JIT-intensive the plant the more profitable it is, but also the less efficient it is. On the other hand, Hypothesis 3(b) is rejected: the *JIT*TOTAL* interaction variable is insignificant in both regressions indicating that plant efficiency and profitability are not more highly correlated with the number of productivity measures of more JIT-intensive plants. Finally, plant efficiency and profitability are negatively related to buffer stock, especially for JIT-intensive plants.

Disaggregating TOTAL

The *TOTAL* variable assumes implicitly that all productivity measures have the same relationship to performance outcomes. There are two a priori reasons why this is unlikely to be correct. First, some productivity measures are fairly common across most plants, whereas others are rather idiosyncratic to the specific plant. This suggests that some types of productivity measures may be more valuable than others and, furthermore, that some productivity measures are only valuable to specific plants. Second, there is evidence in the literature (Callen et al. 2000; Fullerton et al. 2003) that performance outcomes of JIT plants are negatively related to quality.[39] One possible explanation is that plants that adopt more intensive JIT practices invest more resources to enhance process/product quality and/or produce less out-

put to maintain quality than do less JIT-intensive plants. If so, it makes sense to separate the quality productivity measure from other productivity measures.

To minimize these aggregation biases in the *TOTAL* variable, which may be driving some of the results of Table 5, we disaggregate the *TOTAL* in-house productivity measure into three categories: productivity measures that are fairly common among all plants and are probably industry-driven (*STANDARD*); productivity measures that are idiosyncratic to the specific plant (*SPECIFIC*); and the quality productivity measure (*QUALITY*). *STANDARD* is defined as the aggregate of three common productivity measures: total factor productivity, labor productivity, and return on investment.[40] *QUALITY* is a dummy variable set equal to one if the plant employs a quality productivity measure and zero otherwise. *SPECIFIC* is the total number of idiosyncratic productivity measures used by the plant other than *STANDARD* and *QUALITY.* We hypothesize that plant efficiency and profitability are positively related to *STANDARD* and *SPECIFIC* and are either insignificantly or negatively related to *QUALITY.* Thus, in what follows, Hypothesis 3(a) refers only to the *STANDARD* and *SPECIFIC* productivity measures and not to *QUALITY.*

Regressions without interaction terms

Table 6 replicates Table 5 for two kinds of disaggregation.[41] First, disaggregated productivity measures, *STANDARD*, *QUALITY,* and *SPECIFIC*, are used in place of the *TOTAL* variable. Second, the regressions are estimated on the entire sample, the subsample of JIT plants, and the subsample of non-JIT plants, respectively. The reason for this second disaggregation is that regressions estimated on the entire sample assume that the relationships between the disaggregated productivity measures and performance outcomes are homogeneous across technologies.

[CATCH — table 6 near here]

In Table 6, column (1) we see that the coefficients for *STANDARD* and *SPECIFIC* are positive and significant, while the *QUALITY* coefficient is negative but insignificant. These results weakly indicate that plant efficiency is related to a broad range of productivity measures as postulated in Hypothesis 3(a). As before, the negative JIT **[AU: ital?]** coefficient rejects Hypothesis 3(c).

Column (2) lists the parallel profitability regression results. As expected, the coefficient for the JIT technology variable is positive and significant indicating that plants with higher JIT concentration are more profitable, consistent with Hypothesis 3(c). The coefficients for *STANDARD* and *SPECIFIC* (*QUALITY*) are positive (negative) and significant. These results imply that plant profitability, like plant efficiency, is related to a broad range of productivity measures as predicted in Hypothesis 3(a). The buffer stock coefficient is negative and significant.

The overall fit of both regressions for the JIT subsample (columns (3) and (4) of Table 6) is significantly better than that of the full sample, based on adjusted R^2s and F tests. In fact, the adjusted R^2s of the JIT subsample are about four (two) times that of the full sample in the efficiency (profitability) regression. Focusing on the efficiency regression (column (3)), we see that the *JIT* variable is insignificant; the coefficient for *STANDARD* (*QUALITY*) is positive (negative) and significant; the

coefficient for *SPECIFIC*, while positive, is not significant; and the coefficient for the buffer stock is negative and significant. These results are consistent with Hypothesis 3(a) but not Hypothesis 3(c).

The results for the profitability regression (column (4)) are consistent with Hypotheses 3(a) and 3(c). The *JIT* coefficient is positive and significant, the *STANDARD* coefficient is significant and positive, and the *SPECIFIC* coefficient is significant and positive. Nevertheless, *STANDARD* is economically more significant than *SPECIFIC* on the basis of the relative sizes of the coefficient estimates. The coefficients for *QUALITY* and buffer stock are both negative and significant.

In contradistinction, the regressions for the non-JIT subsample (columns (5) and (6)) are insignificant. One needs to be cautious here. Part of the reason for the weak relative showing of the non-JIT plant regressions is likely due to the smaller sample size of the non-JIT subsample, 22 plants by comparison to the JIT subsample of 39 plants, although this is mitigated to some extent by the need to estimate one less parameter (*JIT*) for the non-JIT subsample.

Regressions with interaction terms

As an alternative test of the robustness of the disaggregation across technologies, Table 7 replicates the first two columns of Table 6, inclusive of interaction terms between the JIT concentration index and the independent variables.[42] Both regressions are highly significant. The efficiency regression in Table 7 shows that the *JIT* variable is negative and significant, the *STANDARD* (*QUALITY*) productivity measures are significant and positive (negative), the *SPECIFIC* productivity measure is insignificant, and the buffer stock coefficient is negative and significant. The interaction coefficients follow the same pattern. A standard F-test rejects the hypotheses that the three JIT-interacted productivity measures are identically zero at less than the 5 percent significance level ($F = 3.47$, $p = 0.023$, two-tailed). Overall, the efficiency regression results in Table 7 are consistent with both Hypotheses 3(a) and 3(b) but reject Hypothesis 3(c).

The profitability regression in Table 7 shows that the *JIT* variable is positive and significant, as are the *STANDARD* (*SPECIFIC*) productivity measures. Again, *STANDARD* is economically significant by comparison to *SPECIFIC*. Also, unlike the other two productivity categories, *QUALITY* productivity is significantly negatively related to profitability. *BUFFER* is significantly negative. Of the three JIT-interacted productivity measures, the *JIT*QUALITY* coefficient is negative and significant, the *JIT*STANDARD* coefficient is positive and marginally significant, and the *JIT*SPECIFIC* coefficient is insignificant. An F-test rejects the hypothesis that the three JIT-interacted productivity measures are identically zero ($F = 2.24$, $p = 0.095$, two-tailed). Overall, the profitability regression results in Table 7 are consistent with Hypotheses 3(a), 3(b), and 3(c).[43]

[CATCH — table 7 near here]

Summary of Tables 6 and 7 results

The results for the disaggregated productivity measures in these two tables tell a fairly coherent story despite the various regression approaches. The regression results generally confirm Hypothesis 3(a). Holding technology, plant size, and buffer stocks constant, JIT and non-JIT plants that employ a broader range of standard industry-driven productivity measures and, to a far lesser extent, specific idiosyncratic productivity measures are more efficient and profitable. In contrast, JIT and non-JIT plants that employ a quality productivity measure are less efficient and less profitable. The latter result is likely a consequence of these plants over-investing in quality.

The regression results in Tables 6 and 7 are fully consistent with Hypothesis 3(b). On the basis of the comparison of the JIT subsample with the non-JIT subsample and the full sample in Table 6, and the correlations of plant efficiency and profitability with the JIT interacted productivity measures in Table 7, the efficiency and profitability of more JIT-intensive plants are more highly correlated with the disaggregated productivity measures than less JIT-intensive plants.

Regarding Hypothesis 3(c), the regressions results in Tables 6 and 7 are consistent with more JIT-intensive plants being more profitable but surprisingly less efficient than less JIT-intensive plants, after controlling for plant productivity measures and buffer stock. It appears that despite wasting resources, JIT-intensive plants are still able to generate superior profits relative to plants that are not JIT-intensive.

These regressions also show fairly consistently that plant efficiency and profitability are negatively related to the level of the buffer stock, especially for JIT-intensive plants.

Additional sensitivity analysis

The JIT concentration index includes experience with JIT as one of its 18 principal components. However, studies by Callen et al. 2000 and Fullerton et al. 2003 suggest that experience with JIT may have a more fundamental impact on profitability than the other components of JIT. To test this, we use principal components analysis to aggregate the 17 JIT characteristics other than experience with JIT. This aggregate is then averaged together with experience with JIT to form a new JIT concentration index. Redoing the analysis with this new JIT concentration index yields qualitatively similar results.

Of the 61 plants in the sample, 56 plants belong to different firms and 5 JIT plants belong to two different firms (3 plants belong to one firm and 2 plants to another). If their operations are correlated, plants belonging to the same firm may not be independent observations. Therefore, all tests and regressions were reestimated after dropping consecutive combinations of 3 of these 5 plants from the overall and JIT samples such that no 2 plants belonged to the same firm. This left an overall sample of 58 plants and 36 JIT plants for each combination. Replication of this study for these combinations yields results similar to those reported above.

As stated earlier, non-JIT plants are assumed to take on the minimum JIT technology index value of 17 because of data limitations. However, JIT/TQM data are available for the three plants that were reclassified from JIT to non-JIT. Recomputing the JIT technology index by incorporating the JIT/TQM data for the three plants had no qualitative effects on the results of this study.

7. Conclusion

The management accounting and operations management literatures argue that the adoption of advanced manufacturing practices optimally requires complementary changes in the firm's MAS. This study focuses on JIT manufacturing as an engine of corporate productivity. The results of this study provide evidence that productivity measurement mediates the relationship between performance outcomes and investment in JIT practices. This study implies that a broader range of productivity measurement is beneficial for both JIT and non-JIT plants, although plants that adopt more intensive JIT practices benefit more. Also, this study implies that in order to appropriately measure performance outcomes in a JIT environment, the plant MAS should use industry-driven productivity measures more intensively than idiosyncratic productivity measures.

The negative relationship between profitability/efficiency outcomes and quality productivity measures suggests that JIT-intensive plants overinvest in quality. This study finds that plants that invest more in buffer stock are less efficient and less profitable — especially if these plants use more intensive JIT practices — suggesting the need to closely monitor investment in buffer stock.

Despite the fact that plant profitability and efficiency are highly correlated, JIT plants that implement more intensive JIT practices are more profitable but less efficient than JIT plants that implement less intensive JIT practices, after controlling for productivity measures and buffer stock. This result suggests that despite wasting resources, perhaps by overinvesting in quality, JIT-intensive plants are still able to generate relatively higher profits than plants that are not JIT-intensive.

Like all research, this study has both strengths and weaknesses. Among its strengths is the fact that the data come from a relatively homogeneous industry operating in the same geographical location. This is beneficial because it mitigates (but does not eliminate) the need to control for omitted correlated variables such as industry and organizational structure. Also, by focusing on one industry, the economic context in which MAS numbers are generated is more apparent: a desirable property that is generally missing from accounting research (Bernard and Stober 1989, Lev and Thiagarajan 1993). The data are plant-level rather than firm-level thereby mitigating multiplant aggregation biases inherent in firm-level studies. Most (but not all) of the data are based on objective numbers rather than self-reported and aggregated "soft" survey data. In addition, this study is unique in that it investigates the implications of nonfinancial performance measurement on plant efficiency as well as profitability. In this study, efficiency is measured relative to a (stochastic) industry production frontier that represents the industry best practices benchmark. An additional strength of this study revolves around the issue of causality. Is it that JIT practices, in tandem with a complementary MAS, drive efficiency

and profitability, or is it that efficient and profitable organizations have the resources to adopt JIT and a complementary MAS? The potential endogeneity of the JIT decision was addressed in this study using a 2SLS regression approach.

The study has a number of limitations. The focus on one industry limits the generalizability and applicability of the findings to other industries, as does the limited number of sample observations. The limited JIT experience of the sample observations may also affect the results.[44] The cross-sectional nature of (almost all of) the data restricts the issues that can be addressed — most crucially, the interaction between JIT adoption and the MAS over time (Fullerton et al. 2003). Although the JIT characteristics in this study are fairly comprehensive, they may not reflect actual company practices. In addition, this study analyzes productivity measures independently of other elements of the MAS, thereby disregarding potentially important complementarities.

The limitations of this study call for future research. The most obvious direction is to extend this study to other industries in order to see whether the implications of this study hold more generally. Ideally, the data base should be extended to include compensation contract information in order to explore the direct economic linkages between performance measures and performance outcomes in an advanced manufacturing setting. Data on other elements of the MAS and organizational structure variables would enhance future research in this area. Finally, data based on plants that have longer experience with JIT than the plants in this study would be most beneficial.

Appendix: Efficiency measurement using stochastic production frontiers

Plant-level efficiency in this study is measured by a stochastic production frontier approach. The primary advantage of this method is that it accommodates random errors in the estimation and in the specification of the efficiency measure, thereby allowing for direct statistical testing of the model parameters.[45] The production function is formulated with two independently distributed error components:

$$Y_i = \mathrm{F}(\boldsymbol{X}_i, \boldsymbol{\beta}) \exp\{(v_i - u_i)\} \qquad \text{(A1)},$$

where

Y_i is the (log) output of the i-th plant;[46]

F is the production function;

$\boldsymbol{X}_i$ is a vector of (log) input quantities of the i-th plant;

$\boldsymbol{\beta}$ is a vector of unknown parameters;

v_i are symmetrically distributed error terms typically assumed to be iid $N(0, \sigma_V{}^2)$;

u_i are non-negative one-sided error terms typically assumed to be iid $N^+(:, \sigma_U{}^2)$ where N^+ denotes the truncated normal distribution.

The stochastic production function consists of two parts: a deterministic part $F(\boldsymbol{X}_i, \boldsymbol{\beta})$ common to all plants and a plant-specific part $\exp(v_i)$, which captures random shocks to each manufacturer.

The one-sided error term (u_i) accounts for technical inefficiency.[47] Rewrite (A1) as

$$\exp(-u_i) = Y_i / \{F(\boldsymbol{X}_i, \boldsymbol{\beta}) \exp(v_i)\} \qquad \text{(A2).}$$

Because Y_i is actual production and $\{F(\boldsymbol{X}_i, \boldsymbol{\beta}) \exp(v_i)\}$ denotes maximum feasible production in a stochastic environment reflected by $\exp(v_i)$, it follows that $\exp(-u_i) = 1$ only if the plant produces its maximum feasible production. Otherwise, $\exp(-u_i) < 1$ measures the shortfall of observed production from maximum feasible production, which by definition is technical inefficiency.

The estimation of the stochastic frontier along with the inefficiency term involves specifying the distribution of u_i as well as the form of the production function. Several distributions have been employed in the literature for the one-sided inefficiency disturbance term u_i. Because the literature indicates that the inefficiency rankings are typically robust to the assumed distribution of the one-sided error term, we employ only two in this study, the ubiquitous half normal and the more general truncated normal.[48]

Define $\varepsilon_i = v_i - u_i$. Because the u_i are not directly observable, we follow Jondrow, Lovell, Materov, and Schmidt 1982 and Battese and Coelli 1988 by computing the plant-specific inefficiency as the conditional mean $E\{exp-(u_i|e_i)\}$. **[AU: is E a function? if yes, it should be Rom]** By construction, the conditional mean is greater than or equal to zero; the closer it is to zero, the more inefficient is the plant. With the assumed independence of the distributions of v_i and u_i, computations of the distribution of e_i and of the maximum likelihood estimates of the model parameters are fairly straightforward. The test statistic $\gamma\,(=\sigma_u{}^2/(\sigma_v{}^2 + \sigma_u{}^2))$ indicates whether the one-sided error term is necessary at all. Specifically, it is straightforward to see that $\gamma \to 0$ as either $\sigma_u{}^2 \to 0$ or as $\sigma_v{}^2 \to \infty$. Thus, $\gamma \to 0$ as the symmetric error term dominates the one-sided error term in the determination of ε, implying the absence of technical inefficiency. If γ is insignificantly different from zero, there is no stochastic frontier issue and the production function can be estimated by OLS.

The mean efficiency measure for all plants can be calculated as $E[\exp(-u)]$ **[AU: is E a function?]** where u is distributed truncated normal, $u \sim N^+(\mu, \sigma_u{}^2)$. Given this distributional assumption, our sample yields $E[\exp(-u)]$ **[AU: is E a function?]** $= \{\exp(-\mu + \sigma_u{}^2/2)[1 - \Phi(\sigma_u - \mu/\sigma_u)]\}/[1 - \Phi(-\mu/\sigma_u)] = 0.85$ where $\Phi(.)$ denotes the cumulative (standard) normal distribution. This indicates that, on average, plants in the automotive parts manufacturing industry are 15 percent inefficient relative to the estimated frontier.

Following Horrace and Schmidt 1996, one can also derive a $(1 - \alpha)$ percent confidence interval around the mean.[49] Specifically, if Z_L and Z_U denote the lower and upper critical values, respectively, then at the 95 percent confidence level, $L =$ **[AU: closing braces ok? omitted on ms]** $\{\exp(-\mu + Z_L\sigma_u)\} = 0.69$ and $U =$

$\{\exp(-\mu + Z_U \sigma_u)\} = 0.96$ where $\Phi(Z_L) = \{1 - \alpha/2\ [1 - \Phi(-\mu/\sigma_u)]\}$ and $\Phi(Z_U) = \{1 - (1 - \alpha/2)\ [1 - \Phi(-\mu/\sigma_u)]\}$.

Endnotes

1. The *Journal of Productivity Analysis*, an economics journal, is devoted solely to this topic.
2. On the relationship between productivity and global competitiveness, see Porter 1990 and Bernolak 1997. Typically, productivity is included in managerial accounting textbooks in chapters that emphasize global competitiveness and the new manufacturing environment.
3. We use the term JIT interchangeably with the term JIT/TQM. Although it is possible to adopt TQM practices without JIT, JIT requires significant investment in process and product quality, as emphasized by Flynn, Sakakibara, and Schroeder 1995 and Sim 2001, among others.
4. This objective was frequently emphasized in conversations with plant managers and accountants working in this industry.
5. It was often made clear to us that they were willing to provide productivity data in no small part because such data were mandated by the Canadian federal authorities for their Census of Manufacturing report. This report is published at the highly aggregate country-wide level. The data are unavailable from the authorities at the plant or firm level because of privacy constraints.
6. Ittner and Larcker (2001) raise other potential problems plaguing most of these studies including the absence of controls for the organization's competitive environment, strategy, and organizational design and other omitted correlated variables such as the performance measures used by the organization other than those under study.
7. See Kaplan and Atkinson 1989 (378–82), Neely 1999, Maskell 2000, and Ittner and Larcker 1998 and 2001. Nonfinancial performance measures include those that are completely nonfinancial such as number of engines produced per hour or those that are partially nonfinancial such as value added per worker per day.
8. This element of the maintained hypothesis is debatable, of course. Moreover, there is no corresponding empirical evidence to support it. Nevertheless, the argument provides sufficient conditions for Hypothesis 3(a) to hold.
9. For example, one of the sample firms in Balakrishnan et al. 1996 comprises 3 JIT and 10 non-JIT plants.
10. We do sensitivity analyses on these 5 plants, as described below.
11. Because the types and intensities of JIT characteristics may be systematically related to plant characteristics such as size (White, Pearson, and Wilson 1999), a broader set of JIT characteristics is preferable to a narrower set.
12. We do sensitivity analyses on the three reclassified plants, as described below.
13. We do sensitivity analyses on this combination, as described below.
14. This procedure unavoidably yields a noisy measure of "JITness" for non-JIT plants.
15. This ratio is a productivity measure in the sense that investment is an input and net income an output. Over 90 percent of the productivity measures listed by our sample plants are nonfinancial.
16. Even with a Cobb-Douglas, we end up estimating nine parameters plus an intercept.

17. We also estimated the more general forms $Y_i = \Pi_j A^{(\alpha 0 + JIT.\beta 0)} X_{ij}^{(aj + JIT.\beta j)} \exp\{\varepsilon_i\}$ and $Y_i = \Pi_j A.JIT^{\beta 0} X_{ij}^{(\alpha j + JIT.\beta j)} \exp\{\varepsilon_i\}$. The results were qualitatively similar to those of (1).
18. Defined as total annual 1990 labor costs including gross wages, commissions, and bonuses.
19. Defined as the total annual 1990 cost of purchased fuel and electricity used in manufacturing operations.
20. Defined as the total annual 1990 cost of raw materials and components purchased and used in manufacturing operations.
21. Defined as the sum of annual 1990 book value depreciation, annual interest expense on debt financed physical capital and inventories, and annual equipment rental costs.
22. Although ordinary least squares (OLS) provides consistent estimates of the parameters (with the exception of the constant term), maximum likelihood estimation yields parameter estimates that are more efficient (that is, have smaller standard errors). The point estimate $\gamma = 1$ implies that the stochastic error in the production function is due primarily to inefficiency.
23. We also estimated the production frontier under the common assumption that the u_i are half-normal (not shown) both for the case where the latter error terms are homoscedastic and for the case where they depend on plant size. The results in this paper are not sensitive to the assumed distribution of the u_i nor to the assumption of homoscedasticity. Nevertheless, we present the results for the truncated normal because the half-normal is rejected in favor of the truncated normal ($\mu = 0.112$) at the 1 percent significance level (two-tailed, $t = 3.11$), as indicated in Table 2. All t-, F-, and p-values in this paper are two-tailed, even where the hypothesis is unidirectional.
24. The likelihood ratio test statistic $\lambda = -2\ (L^* - L)$ is distributed approximately $\chi^2(4)$ where L denotes the log likelihood of the unrestricted model and L^* the log likelihood of the restricted model.
25. The capital input is measured primarily by depreciation expense, a rather noisy measure that may explain the insignificance of the capital exponent.
26. This is so at the 90 percent confidence level as well.
27. Also, the efficiency scores are distributed truncated normal so that the tests in Table 3 are only asymptotic. Standard nonparametric tests such as the Wilcoxon are also problematic because the truncated normal is obviously not a symmetric distribution, and these tests presuppose symmetry.
28. *INVENTORY CONTROL* is defined as total number of productivity measures associated with inventory control (excluding *QUALITY*).
29. *TFP* accounts for all inputs whereas *LP* only accounts for the labor input.
30. We thank an anonymous referee for this insight. As this referee suggests, one could further speculate that labor productivity is useful for labor relations/contracting in a unionized setting. The argument that labor costs are collected anyway, thereby making the calculation of *LP* relatively less costly to compute than other measures, is less convincing because the plants in our sample also collect other relevant production costs.
31. It is not necessary to include a size regressor in the profitability regression, because the profit measure is already normalized by plant size.

32. To help account for technology differences, separate means were computed for each of JIT and non-JIT plants.
33. Because the efficiency measure is limited to lie between zero and one, OLS potentially yields biased coefficients. A tobit regression (or truncated regression) approach is generally more appropriate. However, because the efficiency scores in this study never take on the extreme values of zero or one, OLS necessarily yields the same coefficient estimates as a tobit (truncated) regression.
34. Replacing *TOTAL* with *DISTINCT* in this regression and those that follow yields similar results. We examine the regression for multicollinearity using the criteria outlined in Belsley, Kuh, and Welsch 1980. If severe multicollinearity is present, the coefficient estimates, although unbiased, are sensitive to minor changes in the model. The Belsley-Kuh-Welsch diagnostics do not indicate a multicollinearity problem because both the largest variance inflation factor and the largest condition index among the regression variables are less than 2.
35. The instrumental variables in the regression analysis are defined in the negative so that the correlations are positive.
36. This test is described in Greene 2000 (383–7).
37. Again, the Belsley-Kuh-Welsch 1980 diagnostics do not indicate a multicollinearity problem because the largest variance inflation factor and condition index are less than 2.5.
38. Although the JIT decision appears to be endogenous, the similarity between the 2SLS (which accounts for endogeneity) and OLS results indicates that bias to the OLS coefficients is minimal.
39. The textbook literature also warns about the potential negative impact of excessive investment in quality on performance. See Juran and Gryna 1980; McWatters, Morse, and Zimmerman 2001; and Zimmerman 2002.
40. Total factor productivity and return on investment are also highly correlated. We obtain qualitatively similar results after dropping return on investment from the list of productivity measures.
41. Two-stage least squares cannot be used to analyze the relationship between the JIT and non-JIT subsamples because of insufficient degrees of freedom for the non-JIT subsample. The 2SLS coefficient estimates (not tabulated) are quite similar to the OLS estimates for the full and JIT samples.
42. We include interaction terms for all of the independent variables in Table 6, including *BUFFER* and *SIZE*, because the latter two variables are also likely to be driven by the technology. In fact, the JIT plants in our sample are larger and have less buffer stock on average than non-JIT plants.
43. Despite the large number of interaction terms in Table 7, the Belsley-Kuh-Welsch 1980 diagnostics do not indicate a multicollinearity problem because both the largest variance inflation factor and the largest condition index among the regression variables are less than 9.
44. Intuition suggests that the differences found in this study between JIT and conventional plants are likely to increase with more JIT experience.

45. Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977) initiated stochastic frontier production analysis. Greene (1993, 1997) and Kumbhakar and Lovell (2000) provide useful background material.
46. Logs are used if F(.) is assumed to be Cobb-Douglas or translog, for example.
47. A plant is technically inefficient if it could have produced more output with the given level of resources or used less resources to produce a given level of output (or both), irrespective of input and output prices.
48. See Kumbhakar and Lovell 2000 (90) on the robustness of rankings to the assumed distribution of the one-sided error term.
49. This confidence interval for the mean efficiency of all plants is relatively wide. Because the (highly significant) point estimate $\gamma = 1$ implies $\sigma_v^2 = 0$, there is essentially little random error concerning the individual plant efficiency scores. Thus, while we cannot be that confident about the specific efficiency of the average plant, we can be very confident about the efficiency scores of the individual plants. See Horrace and Schmidt 1996 for similar results in a totally different environment. A partial distribution of plant-level efficiency scores is found in Table 3.

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TABLE 1
JIT/TQM characteristics techniques used in JIT plants

JIT/TQM techniques	Mean	s.d.
Kanban	2.82	1.02
Integrated poduct design	3.03	1.22
Integrated suppliers network	2.64	0.99
Plan to reduce setup time	2.34	0.72
Quality circles	2.26	0.75
Focused factory	2.84	1.25
Preventive maintenance programs	4.17	0.39
Line balancing	3.18	0.60
Education about JIT	1.97	0.63
Level schedules	3.46	1.05
Stable cycle rates	3.05	0.72
Market-paced final assembly	3.36	0.93
Group technology	2.18	0.60
Program to improve quality (product)	4.82	0.39
Program to improve quality (process)	4.84	0.37
Fast inventory transportation system	4.03	0.67
Flexibility of worker's skill	2.25	0.59
JIT experience	2.15	1.06

Note:

The table lists mean scores (and standard deviations) of 17 JIT/TQM characteristics and JIT experience for 39 JIT plants. With the exception of JIT experience measured as the number of years since JIT adoption, all other scores are based on a five-point Likert scale where 5 = always used and 1 = never used.

TABLE 2
Estimated stochastic frontier production function

Coefficient	Unrestricted model: Maximum likelihood estimate	Unrestricted model: *t*-ratio	Restricted model: Maximum likelihood estimate	Restricted model: *t*-ratio
α_0	0.820	1.629	0.932	2.121*
α_1	0.148	2.041*	0.035	0.763
α_2	0.619	7.469†	0.414	8.490†
α_3	−0.019*	−0.262*	0.131	3.101†
α_4	0.295	4.711†	0.452	8.687†
β_1	−0.169*	−1.594*	—	
β_2	−0.414*	−2.571*	—	
β_3	0.235	1.991*	—	
β_4	0.351	2.499*	—	
σ^{2}‡	0.016	5.168†	0.044	1.233
γ§	1.000	32.951†	0.847	5.481†
μ#	0.112	3.109†	−0.384*	−0.784*
Log likelihood function	65.219		51.97	
LR test of the one-sided error†, #	6.836*		1.792	
Mean efficiency = E[exp(−*u*)]	0.848†		0.931	

[AU: 3rd decimal?]

Notes:

The estimated unrestricted stochastic frontier production is of the form:

$$\ln(Y) = \alpha_0 + \sum_j \alpha_j \ln(X_j) + \sum_j \beta_j \, JIT{*}\ln(X_j) + \varepsilon_i,$$

where

Y = retail value of annual production,

X_1 = annual fuel costs,

X_2 = annual material costs,

X_3 = annual capital costs,

X_4 = annual labor costs, and

JIT = JIT technology index.

[AU: According to CAR style, order of footnote symbols is *, †, ‡, §, #, **. Please verify. Also, variables are set italic and functions are Roman. Verify all such]

The restricted model assumes $\beta_i = 0$ for all i. **[AU: "for" ok?]**

* Significant at the 5 percent level (two-tailed).

† Significant at the 1 percent level (two-tailed).

‡ σ^2 = estimated variance of compound error term = $\sigma_u^2 + \sigma_v^2$ where σ_u^2 is the estimated variance of the one-sided error term and σ_v^2 is the estimated variance of the symmetric error term.

§ $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$.

\# μ = mean of the truncated normal distribution. Mean efficiency is computed as E[exp(−*u*)] where $u \sim N + (\mu, \sigma_u^2)$.

** The LR (likelihood ratio) statistic has a mixed chi-square distribution.

[AU: corresponding superscript missing from table body. please add]

TABLE 3
The relationship between efficiency scores and plant technology:
Distribution and univariate tests

Panel A: Efficiency scores [**AU: addition of "Panel A" etc. ok?]**

		Efficiency scores			
Plant type	Sample size	Mean	25th percentile	50th percentile	75th percentile
Entire sample	61	0.869	0.813	0.862	0.937
JIT	39	0.856	0.802	0.852	0.910
Non-JIT	22	0.892	0.842	0.881	0.970

Panel B: Tests of differences in efficiency between JIT and non-JIT plants

t-test score = 1.680	*p*-value = 0.106*
Wilcoxon *Z* score = 2.005	*p*-value = 0.045

Panel C: Correlation between efficiency scores and plant technology

Pearson = −0.095	*p*-value = 0.468
Spearman = −0.042	*p*-value = 0.750

Panel D: Correlation between efficiency scores and plant profitability

Pearson = 0.691	*p*-value = 0.000
Spearman = 0.665	*p*-value = 0.000

Notes:

* *p*-values are two-tailed.

Plant (technical) efficiency is measured as the one-sided truncated-normal error term from the estimated unrestricted stochastic frontier Cobb-Douglas production function of Table 2. Plant profitability is measured by earnings before taxes normalized by the value of production at retail.

TABLE 4
Summary statistics of in-house productivity measures categorized by technology*

Productivity measures	Non-JIT plants ($n = 22$) Mean (p-value)†	Non-JIT plants ($n = 22$) Median (p-value)	JIT plants ($n = 39$) Mean (p-value)	JIT plants ($n = 39$) Median (p-value)	Comparison of means t-test (p-value)	Comparison of medians Wilcoxon (p-value)
TFP	0.318	0.000	0.949	1.000	5.85	5.22
	(0.005)	(0.016)	(0.000)	(0.000)	(0.00)	(0.00)
LP	0.955	1.000	1.00	1.000	1.00	1.30
	(0.000)	(0.000)	(0.000)	(0.000)	(0.33)	(0.20)
ROI	0.318	0.000	0.923	1.000	5.48	4.92
	(0.005)	(0.016)	(0.000)	(0.000)	(0.00)	(0.00)
QUALITY	0.227	0.000	0.974	1.000	7.87	6.08
	(0.022)	(0.063)	(0.000)	(0.000)	(0.00)	(0.00)
TOTAL	3.182	2.000	5.949	5.000	5.59	4.36
	(0.000)	(0.000)	(0.000)	(0.000)	(0.00)	(0.00)
DISTINCT	2.591	2.000	5.410	5.000	5.70	4.61
	(0.000)	(0.000)	(0.000)	(0.000)	(0.00)	(0.00)
INVENTORY CONTROL	0.364	0.000	1.026	1.000	2.94	2.02
	(0.002)	(0.008)	(0.000)	(0.000)	(0.01)	(0.04)

(The table is continued on the next page.)

TABLE 4 (Continued)

Notes:

* Each in-house productivity measure takes on a value of one if adopted by the plant and zero otherwise.

† Bracketed figures are two-tailed *p*-values.

TFP = total factor productivity = total output/total input;

LP = labor productivity = total output/labor;

ROI = net income/total investment (or capital);

QUALITY = quality of output;

= number of acceptable units/total processing costs + total correction cost;

TOTAL = total number of productivity measures used by the plant;

DISTINCT = total number of distinct productivity measures;

INVENTORY = total number of productivity measures associated with inventory *CONTROL* control (excluding *QUALITY*).

TABLE 5
Regressions of plant efficiency and profitability on the number of productivity measures

	EFFICIENCY			*PROFIT*		
Variables	(1) OLS	(2) 2SLS*	(3) OLS	(4) OLS	(5) 2SLS	(6) OLS
Intercept	0.869	0.869	0.875	0.199	0.199	0.198
	(0.000)†	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JIT	−0.049	−0.083	−0.064	0.105	0.070	0.090
	(0.116)	(0.028)	(0.052)	(0.000)	(0.038)	(0.004)
TOTAL	0.015	0.016	0.014	0.020	0.021	0.019
	(0.009)	(0.006)	(0.008)	(0.003)	(0.000)	(0.005)
SIZE	0.015	0.023	0.009	—	—	—
	(0.376)	(0.204)	(0.574)			
BUFFER	−0.345	−0.319	−1.507	−0.454	−0.503	−1.238
	(0.439)	(0.480)	(0.011)	(0.275)	(0.234)	(0.034)
*JIT*TOTAL*	—	—	−0.006	—	—	0.011
			(0.705)			(0.477)
*JIT*SIZE*	—	—	−0.103	—	—	—
			(0.057)			
*JIT*BUFFER*	—	—	−5.208	—	—	−3.108
			(0.003)			(0.054)
F-value	2.66	3.25	3.28	13.01	9.54	8.95
	(0.042)	(0.018)	(0.006)	(0.000)	(0.000)	(0.000)
Adj. R^2	0.10	0.13	0.21	0.38	0.30	0.40

(The table is continued on the next page.)

TABLE 5 (Continued)

Notes:

$$EFFICIENCY = \alpha_0 + \alpha_1 JIT + \alpha_2 TOTAL + \alpha_3 SIZE + \alpha_4 BUFFER + \alpha_5 JIT{*}TOTAL + \alpha_6 JIT{*}SIZE + \alpha_5 JIT{*}BUFFER$$

$$PROFIT = \beta_0 + \beta_1 JIT + \beta_2 TOTAL + \beta_3 BUFFER + \beta_4 JIT{*}TOTAL + \beta_5 JIT{*}BUFFER$$

?

EFFICIENCY = stochastic frontier technical efficiency scores;

PROFIT = earnings before taxes normalized by the value of production at retail prices;

JIT = JIT technology index;

TOTAL = total number of productivity measures used by the plant;

SIZE = log of the value of production at retail prices;

BUFFER = plant buffer stock defined as average inventory value.

* Instrumental variables for the JIT technology index in the 2SLS regression include prior period ending work-in-process inventory, finished goods inventory, and fuel inventory (all normalized by sales). To mitigate multicollinearity induced by the cross-product terms and to enhance interpretation of the coefficient estimates, all variables in this table are demeaned. The sample size is 61 observations in all regressions.

† Bracketed figures are two-sided *p*-values.

TABLE 6
OLS regressions of plant efficiency and profitability on disaggregated productivity measures

	Entire sample		JIT plants		Non-JIT plants	
Variable	(1) *EFFICIENCY*	(2) *PROFIT*	(3) *EFFICIENCY*	(4) *PROFIT*	(5) *EFFICIENCY*	(6) *PROFIT*
Intercept	0.869	0.199	0.859	0.182	0.910	0.168
	(0.000)*	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JIT	−0.050	0.102	−0.002	0.157	—	—
	(0.108)	(0.001)	(0.963)	(0.000)		
STANDARD	0.043	0.055	0.095	0.087	−0.004	0.033
	(0.071)	(0.020)	(0.002)	(0.000)	(0.905)	(0.457)
QUALITY	−0.071	−0.072	−0.264	−0.254	0.086	0.028
	(0.216)	(0.190)	(0.001)	(0.000)	(0.323)	(0.797)
SPECIFIC	0.015	0.019	0.007	0.011	0.009	0.014
	(0.057)	(0.013)	(0.312)	(0.033)	(0.792)	(0.758)
SIZE	0.013	—	−0.019	—	0.067	—
	(0.457)		(0.265)		(0.037)	
BUFFER	−0.589	−0.713	−2.639	−1.881	0.858	0.033
	(0.222)	(0.108)	(0.002)	(0.004)	(0.197)	(0.964)
F-value	2.16	8.54	5.71	22.54	1.72	1.28
	(0.061)	(0.000)	(0.000)	(0.000)	(0.186)	(0.316)
Adj. R^2	0.10	0.39	0.43	0.74	0.15	0.05

(The table is continued on the next page.)

TABLE 6 (Continued)

Notes:

$$EFFICIENCY = \alpha_0 + \alpha_1 JIT + \alpha_2 STANDARD + \alpha_3 QUALITY + \alpha_4 SPECIFIC + \alpha_5 SIZE$$

$$PROFIT = \beta_0 + \beta_1 JIT + \beta_2 STANDARD + \beta_3 QUALITY + \beta_4 SPECIFIC$$

EFFICIENCY	=	stochastic frontier technical efficiency scores;
PROFIT	=	earnings before taxes normalized by the value of production at retail prices;
JIT	=	JIT technology index;
STANDARD	=	number of labor productivity, total factor productivity, and ROI performance measures used by the plant;
QUALITY	=	1 if the plant uses the quality productivity measure and 0 otherwise;
SPECIFIC	=	number of productivity measures used by the plant excluding standard and quality;
SIZE	=	log of the value of production at retail prices;
BUFFER	=	plant buffer stock defined as the sum of the average **[AU: value of?]** work in process, finished goods, and fuel inventories. **[AU: is this BUFFER effectively the same as BUFFER in Table 5?]**

[AU: CAR prefers to reduce duplication among table notes as much as possible. Okay to delete EFFICIENCY, PROFIT, JIT, SIZE, and perhaps BUFFER and insert "other variables are as defined in Table 5"?]

* Bracketed figures are two-sided *p*-values.

TABLE 7
OLS regressions of plant efficiency and profitability on disaggregate productivity measures adjusted for technology

	EFFICIENCY		*PROFIT*	
Variables*	Coefficient	*p*-value†	Coefficient	*p*-value
Intercept	0.873	(0.000)	0.198	(0.000)
JIT	−0.075	(0.025)	0.090	(0.004)
SIZE	0.013	(0.395)	—	—
BUFFER	−1.772	(0.003)	−1.450	(0.018)
STANDARD	0.078	(0.003)	0.076	(0.006)
QUALITY	−0.221	(0.009)	−0.238	(0.008)
SPECIFIC	0.009	(0.368)	0.017	(0.103)
*JIT*BUFFER*	−6.413	(0.000)	−3.644	(0.031)
*JIT*SIZE*	−0.106	(0.038)	—	—
*JIT*STANDARD*	0.205	(0.013)	0.115	(0.167)
*JIT*QUALITY*	−0.768	(0.004)	−0.662	(0.016)
*JIT*SPECIFIC*	−0.003	(0.924)	−0.009	(0.740)
F-value	3.55	(0.001)	6.54	(0.000)
Adj. R^2	0.32		0.45	

Notes:

* To mitigate multicollinearity induced by the cross-product terms and to enhance interpretation of the coefficient estimates, all variables in this table are demeaned.

† Bracketed figures are two-tailed *p*-values.

EFFICIENCY = technical efficiency score (one-sided error term) obtained from the estimated unrestricted stochastic frontier Cobb-Douglas production function of Table 2.

Other variables are as defined in Tables 5 and 6.

Figure 1 Optimal number of productivity measures JIT versus non-JIT plants

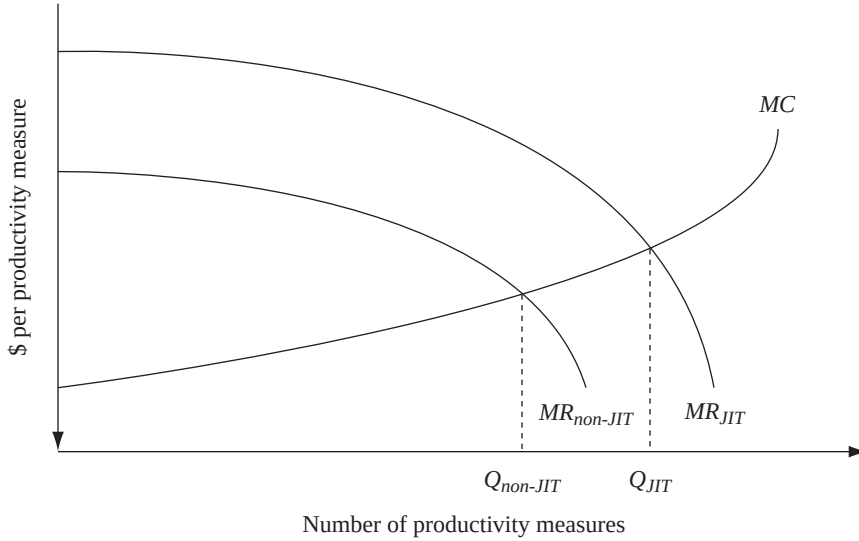

Figure 2 Optimal versus undervalued number of productivity measures