PRODUCTIVITY RACES I:
Are Some Productivity Measures Better Than Others?

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December 1996

Abstract:

In this study we construct twelve different measures of productivity at the plant level and test which measures of productivity are most closely associated with direct measures of economic performance. We first examine how closely correlated these measures are with various measures of profits. We then evaluate the extent to which each productivity measure is associated with lower rates of plant closure and faster plant growth (growth in employment, output, and capital).

All measures of productivity considered are credible in the sense that highly productive plants, regardless of measure, are clearly more profitable, less likely to close, and grow faster. Nevertheless, labor productivity and measures of total factor productivity that are based on regression estimates of production functions are better predictors of plant growth and survival than factor share-based measures of total factor productivity (TFP). Measures of productivity that are based on several years of data appear to outperform measures of productivity that are based solely on data from the most recent year.

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I. Introduction

Economists and practitioners have always been interested in how to generate more output with the same inputs, that is, how to increase productivity. The impacts of education, scientific research, and government policy on productivity have been researched extensively. As old as this research, however, is the debate on how to measure productivity (cf., Bartelsman and Dhrymes, 1992; Olley and Pakes, 1992; and Griliches and Mairesse, 1995). The intent of this study is to construct many measures of plant-level productivity from the same data and to examine which measures are most closely associated with the economic performance of the plant: is the plant profitable? does it remain in operation? does it grow? This study is like a horse race -- the different measures of productivity, one might say, are the horses.

The database for this study is an extract of the surveys of the textile plants in the US Census Bureau’s Longitudinal Research Database (LRD). Our extract consists of data from more than 11,000 plants over a period of 21 years (1972-1992). This database contains information on the capital stock, number of employees, material usage, and output of these plants. Therefore, measures of the ratio of output to inputs -- productivity -- can be constructed. Output measures are all revenue-based, which implicitly assumes that the relative value of different types of outputs can be measured by their relative price. In an industry with large and variable product markups, there may be substantial measurement error associated with a revenue-based measure of output because relative price may not reflect relative value.[1] This study uses data from the textile industry, as this industry is known as being competitive relative to other manufacturing industries. Therefore, the problem of measurement error in output due to markups is minimized.

The measures of productivity are labor productivity (output per employee) and two versions of total factor productivity (TFP). TFP is the ratio of output to an index of different types of inputs. In measuring TFP, there are two theoretically distinct methods for computing the index of inputs, distinguished by the different methods for determining the weights assigned to different types of inputs. The first method weights different types of inputs on the basis of their relative ability to predict output through regression analysis (hereafter, the regression-based method). The second method weights the different types of inputs on the basis of their share of production costs (hereafter, the factor share-based method).

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[1] **For example, a cement manufacturer in a small market may be able to charge a large mark-up because it is the only supplier in town. In this case, a revenue- based measure of output overstates the amount of cement that is actually being produced, which leads to the conclusion that the manufacturer is highly productive when in fact it just a monopolist.**

For this analysis, two distinct concepts of production are relevant. In the first, the plant uses labor and capital to produce value added (a value-added production function); in the second, the plant uses labor, capital, and materials to produce total value of shipments (a total value of shipments production function). This yields a total of six theoretically distinct measures of productivity -- labor productivity, factor share-based TFP, and regression-based TFP computed for both value added and total value of shipments as the measures of output.[2] For this part of the study, we use gross book value as the measure of capital. The second part of the study will focus on different measures of capital and their impacts on the measures of productivity.

In order to evaluate the alternative productivity measures, we ask: How correlated are the different measures of productivity with each other, and how correlated are they with various measures of profits?   We then examined how closely associated the productivity measures are with alternative measures of economic performance (such as faster rates of investment, output growth and job creation, and lower rates of plant closures). In order for a productivity measure -- or group of measures -- to *win a race*, it must have consistently outperformed the other measures in terms

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[2] **For a detailed exposition of the theoretical issues behind each of these measures see Dwyer, 1995c.**

of predicting the different measures of economic performance.

Previous work has demonstrated that there is large variability in the year-to-year productivity of a plant (Dwyer, 1995b and 1996). Presumably, it is the long-term, sustainable component of a plant’s productivity that matters; plant closure decisions should be based on the plant’s long-term performance trend, rather than the plant’s performance in any one year. If this is the case, then a measure of productivity that is based on three years of data should be a better predictor of plant closures than a measure based solely on the plant’s performance in the most recent year. This is the last hypothesis that we test.

The next section of this paper describes the data and the different measures of productivity. The third section describes the correlations among the different productivity measures and different measures of profitability. Sections IV and V compare the ability of different measures of productivity to predict plant closures and examine the extent to which the different measures are associated with firm growth. Section VI tests whether averaging productivity over time yields a better measure of productivity.

II. Data and Productivity Measures

Data:

Our database, an extract of the LRD, includes plants in 22 different four-digit textile industries from 1972 to 1992. The panel is highly unbalanced. This results from plants entering and exiting as well as from small plants having been sampled with a probability of less than one in non-census years. The appendix contains a description of the sampling methods as well as a discussion of the construction of each variable.

In evaluating the measures of productivity, we worked with the pre-1988 data as well as the full sample, because the 1988-1992 data is expected to have a less reliable measure of capital than the earlier period.[3] The measurement problem in the 1988-1992 data could bias the results against measures of productivity that place a heavy weight on capital. Therefore, we looked at both the full sample and the pre-1988 sample, for which reliability of the capital measure is less of an issue, to see if this is indeed the case.

Productivity Measures:

Productivity is defined as the ratio of output to inputs. In order to make this definition operational one must construct an index of inputs that is appropriate to the

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[3] **The Census did not collect information on capital retirements in 1986 and 1988-1991. As a result, book value of capital is computed in these years as if there are no retirements (see Appendix).**

measure of output. Using Census data, there are two reasonable measures of output: total value of shipments adjusted for changes in the value of inventories (*TVS*) and value added (*VA*), which is *TVS* minus material costs. The Cobb-Douglas production function provides a useful framework for constructing appropriate indices of inputs:

where Y is a measure of output, X_i is an input and s_i is the elasticity of output with respect to the input (output increases by s_i percent for a one percent increase in X_i.). A is known as total factor productivity. In order to interpret A as the ratio of output-to-inputs (productivity), the production function must exhibit constant returns to scale,

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same output-to-input ratio -- the same productivity -- will have differing A's. Therefore, this assumption of constant returns to scale is either imposed on the data or returns to scale are measured as being approximately constant.

The first standard method for estimating the residual is to take the factor shares -- the costs of a given input as a percentage of the value of output -- as estimates of the elasticities of output with respect to a given input, s_i..

This methodology is based on the theoretical result that under the assumptions of constant returns to scale, a competitive market, and cost minimization the factor shares will equal the elasticity of output with respect to the relevant input. Given measures of the Y, X_i, and s_i for all i, one can then solve for the A of each plant, thus calculating a plant's productivity. It is straightforward to measure what share of output is represent by labor costs and material costs. It is not clear, however, how to measure the cost of capital inputs, which is necessary to compute capital's factor share.[4] The convention is to invoke the assumption of constant returns to scale ( ), which implies that the factor share of capital is one minus the sum of the other factor shares.

Another approach is to estimate econometrically the s_i 's via Cobb-Douglas production functions.[5] Under this approach one regresses the log(Y_i **) onto the log(X_i)'s, and uses the respective coefficient estimates for the s_i in computing the *A* for each plant (hereafter, the regression-based measure). Under this approach, one generally measures nearly constant**

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[4] One can calculate the costs of capital, but doing so requires making assumptions about the rate depreciation of capital and the opportunity costs of capital, which are difficult to justify.

[5] There are more complicated production functions that one can estimate (a translog or a constant elasticity of substitution), but it is generally agreed that, unless your theory requires a more complicated functional form, the gain from estimating one is marginal (cf. Bartelsman and Dhrymes, 1992, or Griliches and Mairesse, 1995).

returns to scale, which allows one to interpret the computed *A* as a measure of the ratio of output to inputs -- productivity.

Finally, another approach is to measure labor productivity, which assumes that the elasticity of output with respect to labor is one, and that all the others are zero. While theoretically questionable, labor productivity is generally agreed to have less measurement error than TFP, because we are much better at measuring labor than capital.

In this study, we constructed each of these three measures twice. First, we use value added as the measure of output and total employment and capital as measures of inputs. Second, we use total value of shipments adjusted for changes in the value of inventories as the measure of output and total employment, capital and real cost of materials purchased as measures of inputs. Thus we end up with the following six measures of productivity:

Regression-based value-added TFP:

where s_l and s_k are the regression estimates of the elasticities of output with respect to the inputs.

Factor share-based, value-added TFP:

where *VA* is value added, *L* is total employment, *K* is gross book value of capital and s_l is payroll divided by output.

Value-added labor productivity:

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note that this is arbitrarily setting s_l to one and s_k to zero.

Regression-based, total value of shipments TFP:

where s_l, s_K and s_m are the regression estimates of the elasticities of output with respect to the inputs.

Factor share-based, total value of shipments TFP:

where *TVS* is total value of shipments, *L* is total employment, *K* is gross book value of capital, s_l is payroll divided by *TVS*, and s_m is the cost of materials divided by *TVS*.

Total value of shipments labor productivity:

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note that this is arbitrarily setting s_L to one while setting s_k and s_m to zero. Of the six measures of productivity, this is the most problematic, because it ignores material inputs which account for about 50 percent of the cost of producing textiles. Nevertheless, it is of interest because it corresponds to the most common firm-level measure of productivity -- sales per employee.

Implementation:

In order to compute *STFP* and *STTFP*, we begin with factor share measures, which are the cost of the input divided by *VA* (for *STFP*) or *TVS* (for *STTFP*). In the calculation of labor share, we use total payroll plus voluntary and legally required supplemental labor costs to represent labor costs. We use the cost of purchased materials for the cost of materials. These cost measures allowed us to obtain estimates of the factor shares for each plant in each year. In order to create one measure of each factor share for each industry throughout the time period, we take the weighted average of this measure, where the weights are real *VA* (for the value-added based measures) and real *TVS* (for the total value of shipments based measures). The factor shares for each industry are reported in Table II.1.

In order to compute the regression-based measures of productivity, *TFP* and *TTFP*, we begin with regression estimates of each s_i,, for both a value-added production function and a total value of shipments production function.

We estimate a value-added Cobb-Douglas production function:

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for each four-digit industry. The subscripts, *i*, *t,* and *r*, denote the plant, time period, and region respectively. Lower-case letters denote logarithms. The indicator variable, I_{irt}, is defined as:

$$I_{irt} = \begin{cases} 1 & \text{if year = t and region = r,} \\ 0 & \text{otherwise,} \end{cases}$$

where region 1 is the mid-Atlantic states (NY, NJ and PA), region 2 is the southern states (VA, WV, NC, SC, GA, FL, KY, TN, AL, MS) and region 0 is all other states. These indicator variables are included to take into account business cycle effects. Table II.2 summarizes the results of these regressions.

For the *TTFP*, we estimate a total value of shipments Cobb-Douglas production function:

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for each four-digit industry. The results for these regressions are in Table II.3. Observe that for both total value of shipments and value-added production functions, the coefficient estimates are plausible (the capital coefficient is always greater than 0) and the production functions exhibit constant or close to constant returns to scale. Additionally, the estimate of the elasticity of output with respect to labor is consistently larger than the corresponding factor share. Therefore, the regression-based measures of productivity place a larger weight on labor inputs than the factor share-based measures.

To summarize, six measures of productivity are tested (labor productivity, regression-based *TFP*, and factor share-based *TFP* -- computed with total value of shipments and value added as the measures of output). Finally, we run the analysis twice -- on the whole data set and the pre-1988 data set -- because the measure of capital is problematic after 1987.

Table II.1: Factor shares (size weighted)

Sic	Payroll/VA	Payroll/TVS	Material Costs/TVS
2211	0.61	0.29	0.52
2221	0.58	0.27	0.54
2231	0.56	0.26	0.54

2241	0.55	0.30	0.45
2251	0.49	0.28	0.44
2252	0.58	0.29	0.50
2253	0.54	0.31	0.44
2254	0.63	0.31	0.50
2257	0.54	0.21	0.62
2258	0.51	0.20	0.62
2259	0.63	0.33	0.47
2261	0.58	0.27	0.54
2262	0.54	0.19	0.65
2269	0.51	0.19	0.64
2273	0.41	0.13	0.68
2282	0.55	0.18	0.68
2283	0.60	0.23	0.62
2295	0.55	0.23	0.59
2296	0.43	0.13	0.71
2297	0.43	0.21	0.52
2298	0.50	0.28	0.44
2299	0.54	0.29	0.49

Table II.2 Estimates of value-added Cobb-Douglas production functions[6]

SIC	a	b	a+b	R^2
2211	0.838	0.156	0.994	0.892
	(.0148)	(.0115)	(.0082)	
2221	0.792	0.179	0.971*	0.863
	(.0108)	(.0085)	(.0067)	
2231	0.708	0.257	0.965*	0.877
	(.0247)	(.0198)	(.0137)	
2241	0.779	0.182	0.960*	0.854
	(.0168)	(.0122)	(.0111)	
2251	0.861	0.162	1.023	0.859
	(.0210)	(.0172)	(.0132)	
2252	0.870	0.176	1.046*	0.850
	(.0164)	(.0121)	(.0097)	
2253	0.633	0.321	0.954*	0.840
	(.0105)	(.0083)	(.0070)	
2254	0.866	0.134	1.000	0.850
	(.0334)	(.0244)	(.0210)	
2257	0.777	0.171	0.949*	0.816
	(.0135)	(.0105)	(.0084)	
2258	0.763	0.244	1.008	0.836
	(.0189)	(.0142)	(.0115)	
2259	0.580	0.370	0.950*	0.887
	(.0384)	(.0322)	(.0215)	
2261	0.865	0.148	1.013	0.893
	(.0232)	(.0177)	(.0133)	
2262	0.825	0.167	0.992	0.887
	(.0180)	(.0139)	(.0100)	
2269	0.855	0.159	1.014	0.825
	(.0257)	(.0200)	(.0156)	
2273	0.781	0.228	1.009	0.823
	(.0173)	(.0138)	(.0091)	
2282	0.778	0.208	0.986	0.830
	(.0202)	(.0151)	(.0122)	
2283	0.870	0.136	1.007	0.814
	(.0113)	(.0082)	(.0075)	
2295	0.851	0.176	1.027*	0.837
	(.0224)	(.0167)	(.0132)	
2296	0.908	0.186	1.093	0.714
	(.0695)	(.0625)	(.0480)	

[6] The standard errors are in parentheses, which should be interpreted with caution because the procedure does not take into account the serial correlation in the error term. The * in column four denotes that the hypothesis of constant returns to scale can be rejected with 95 percent certainty.

2297	0.727 (.0259)	0.259 (.0168)	0.986 (.0168)	0.834
2298	0.816 (.0255)	0.188 (.0201)	1.003 (.0145)	0.860
2299	0.730 (.0153)	0.267 (.0117)	0.996 (.0093)	0.854

Table II.3: Estimates of a total value of shipments Cobb-Douglas production function.[7]

SIC	a	b	g	a+b+g	R^2
2211	0.3741	0.0504	0.5572	0.9817*	0.9694
	(.0099)	(.0064)	(.0080)	(.0043)	
2221	0.3332	0.1032	0.5208	0.9572*	0.9601
	(.0068)	(.0047)	(.0051)	(.0062)	
2231	0.4333	0.1502	0.3719	0.9554*	0.9507
	(.0189)	(.0137)	(.0117)	(.0092)	
2241	0.4257	0.0934	0.4436	0.9626*	0.9440
	(.0115)	(.0078)	(.0089)	(.0067)	
2251	0.3981	0.0516	0.5488	0.9985	0.9513
	(.0147)	(.0101)	(.0116)	(.0075)	
2252	0.4452	0.0747	0.4858	1.058	0.9587
	(.0099)	(.0061)	(.0074)	(.0047)	
2253	0.3830	0.1662	0.3989	0.9481*	0.9357
	(.0073)	(.0062)	(.0044)	(.0109)	
2254	0.4529	0.0960	0.4246	0.9735*	0.9445
	(.0230)	(.0155)	(.0153)	(.0111)	
2257	0.3747	0.0966	0.4724	0.9437*	0.9451
	(.0087)	(.0063)	(.0045)	(.0107)	
2258	0.4179	0.1197	0.4485	0.9861*	0.9511
	(.0118)	(.0089)	(.0062)	(.0068)	
2259	0.3011	0.2077	0.4469	0.9557*	0.9584
	(.0262)	(.0207)	(.0209)	(.0128)	
2261	0.4198	0.0870	0.4839	0.9906	0.9598
	(.0165)	(.0113)	(.0108)	(.0081)	
2262	0.3657	0.0572	0.5665	0.9895	0.9651
	(.0123)	(.0089)	(.0075)	(.0061)	
2269	0.4357	0.0734	0.5012	1.0103	0.9540
	(.0155)	(.0109)	(.0092)	(.0084)	
2273	0.2578	0.0631	0.6679	0.9887*	0.9705
	(.0082)	(.0061)	(.0058)	(.0038)	
2282	0.3989	0.1326	0.4414	0.9729*	0.9625
	(.0109)	(.0082)	(.0055)	(.0063)	
2283	0.3955	0.0619	0.5217	0.9791*	0.9568
	(.0063)	(.0040)	(.0045)	(.0036)	
2295	0.3514	0.0784	0.5697	0.9995	0.9531
	(.0158)	(.0093)	(.0116)	(.0072)	
2296	0.1803	0.1006	0.6491	0.9300*	0.9564
	(.0238)	(.0209)	(.0169)	(.0155)	
2297	0.3029	0.1187	0.5485	0.9701*	0.9558

[7] The standard errors are in parentheses, which should be interpreted with caution because the procedure does not take into account the serial correlation in the error term. The * in column four denotes that the hypothesis of constant returns to scale can be rejected with 95 percent certainty.

	(.0150)	(.0092)	(.0120)	(.0084)	
2298	0.3659	0.0699	0.5642	1.0000	0.9564
	(.0168)	(.0112)	(.0145)	(.0078)	
2299	0.3710	0.1262	0.5096	1.0068	0.9541
	(.0097)	(.0068)	(.0071)	(.0052)	

III. Correlations between different measures of productivity and different measures of profitability.

In this section, we examine how correlated the productivity measures are with each other, and how correlated they are with different measures of profits. Before the correlation coefficients are computed, the measures are standardized. We took the log of each measure and then subtracted out the industry mean of that measure in each year. Therefore, if a plant has a standardized *tfp* (recall that lower case letters denote logarithms) of 0.35, this implies that the plant is 35 percent above the average of its four-digit industry in that year.

Table III.1 presents a matrix of correlation coefficients between the measures. All the productivity measures are highly correlated. The regression-based measures (*tfp* and *ttfp*) are more closely associated with the labor productivity measures (*lp* and *tlp*) than are the factor share-based measures (*stfp* and *sttfp*). This is what one would expect, because the regression-based measures of productivity place a larger weight on labor productivity than the factor share-based measures.

The measure of productivity that is the least correlated with the other measures is the total value of shipments per employee, *tlp*. This is to be expected, as *tlp* is the only measure of productivity that ignores material inputs, which account for about 50 percent of sales. This suggests that the most common firm level measure of productivity -- sales per employee -- may be rather problematic. The correlation between *tfp* and *tlp* is .6. One interpretation of the magnitude of this correlation coefficient is as follows: If you regress *tfp* onto *tlp*, then 36 ($.6^2$) percent of the variation in *tfp* would be explained by *tlp*.[8] The rank correlations tell substantively the same story (Table III.2).[9]

The next question is, how correlated are these measures of productivity with various measures of profits? We compute profit rates as value added minus payroll, divided by four different measures of scale: number of employees, value added, total value of shipments, and book value of capital. Profit per unit capital is closely aligned with return on assets. Theoretically, therefore, profit per unit capital is the most appropriate profit measure. This measure, however, suffers from measurement error in the

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[8] We are invoking the fact that the R^2 of a regression with one independent variable is equal to the square of the correlation coefficient of the independent and dependent variables.

[9] A rank correlation is the correlation coefficient between the ranks of the two different measures; that is, one creates a ranking variable where the plant with the largest productivity gets 1, the next largest get 2 and so on, and then one computes the correlation coefficient between the ranking variables. This measure of correlation is not sensitive to the functional form of the measure. The rank correlation between two productivity measures that are measured in logs is the same as the rank correlation between two productivity measures that are in levels.

capital variable. Therefore, it is useful to look at the other measures as well.

Profit per employee is most closely associated with value added per employee, *lp*, as one would expect since they share the same denominator. In terms of profit per value added, *lp* performs the best; whereas for profit per sales, the *ttfp* performs the best. Note that the correlation coefficients are small; the largest R^2 (the square of the correlation coefficients of profit per employee and *tfp*) associated with a measure of profit and regressed on a measure of productivity is about 25 percent. The rank correlations are much higher (Table III.4): Regressing a plant's rank in terms of productivity onto its rank in terms of profits yields R^2's as high as 69 percent (the square of the correlation coefficient of profit per employee and *lp*). Our interpretation of this finding is that the highly productive plants are highly profitable, but there is not a linear relation between profits and productivity, which results in the rank correlation being higher.

To summarize, measures of productivity are highly correlated with themselves and with measures of profitability. The most common measure of productivity at the firm level, Sales per Employee, is the least correlated with the other measures and with measures of profitability, suggesting that this measure is problematic due to the fact that it ignores material inputs into the production process.

Table III.1 Correlation matrix of productivity measures

	tfp	*stfp*	*lp*	*ttfp*	*sttfp*	*tlp*
tfp	1.00	0.93	0.95	0.77	0.65	0.59
stfp	0.93	1.00	0.78	0.71	0.72	0.41
lp	0.95	0.78	1.00	0.73	0.52	0.69
ttfp	0.77	0.71	0.73	1.00	0.89	0.52
sttfp	0.65	0.72	0.52	0.89	1.00	0.21
tlp	0.59	0.41	0.69	0.52	0.21	1.00

Table III.2 Rank correlation matrix of productivity measures

	tfp	*stfp*	*lp*	*ttfp*	*sttfp*	*tlp*
tfp	1.00	0.91	0.92	0.86	0.75	0.61
stfp	0.91	1.00	0.72	0.78	0.84	0.41
lp	0.92	0.72	1.00	0.79	0.58	0.71
ttfp	0.86	0.78	0.79	1.00	0.85	0.55
sttfp	0.75	0.84	0.58	0.85	1.00	0.24
tlp	0.61	0.41	0.71	0.55	0.24	1.00

Table III.3 Correlations between different measures of productivity and different measures of profits

	tfp	*stfp*	*lp*	*ttfp*	*sttfp*	*tlp*
Profit/Va	0.27	0.24	0.26	0.09	0.07	0.06
Profit/TE	0.53	0.43	0.57	0.49	0.36	0.47
Profit/Sales	0.20	0.18	0.21	0.38	0.33	0.14
Profit/Capital	0.05	0.04	0.06	0.05	0.03	0.05

Table III.4 Rank correlations of between different measures of productivity and different measures of profits

	tfp	*stfp*	*lp*	*ttfp*	*sttfp*	*tlp*

Prof/VA	0.78	0.64	0.81	0.66	0.52	0.54
Prof/TE	0.79	0.64	0.83	0.68	0.53	0.57
Profit/Sales	0.70	0.61	0.70	0.63	0.60	0.23
Profit/Capital	0.50	0.40	0.52	0.43	0.31	0.34

Section IV: Associations with closure rates

Many papers have showed that productivity measured at the firm or plant level predicts plant or firm closure: The plants measured as having a low level of productivity in year *t* are more likely to close in the following years (Baily, Hulten and Campbell, 1992; Olley and Pakes, 1992; Griliches and Regev, 1994; and Dwyer, 1995a). In our study, we measure closure rates over census year pairs (72 & 77, 77 & 82, 82 & 87, 87 & 92). A closure is defined as a plant not being in any manufacturing industry at the end of a census year pair.[10]

We are examining the extent to which a productivity measure in one census year is inversely related to exit from manufacturing in the next census year. Since this is an exploratory study, we impose as little structure upon the data as possible in order to let the data speak for itself. Therefore, we rank plants into deciles according to their productivity ranking within their industry and compute closure rates out of those deciles. The plants in the 0 to

[10] **By working across census year pairs, one avoids sample selection issues, because every plant is sampled with probability one in each census year.**

10th percentiles in terms of their productivity in their four-digit industry are grouped into the first decile; plants in the 11th to 20th percentiles are grouped into the second decile and so on. We perform the grouping for each of the six productivity measures in each census year, and compute the closure rates for each of these 10 groups. This is a form of a non-parametric regression, because we are in essence regressing a closure variable onto *tfp*, without imposing a functional form on the data.

Table IV.1 presents the mean closure rates by decile for *ttfp*. Note that the plants in the higher deciles are less likely to close than plants in the lower deciles. Table IV.2 presents the closure rates *sttfp*. With this measure, the higher deciles also have lower closure rates, but the discrepancy between the closure rate of the high decile and low decile plants is smaller. This suggests that the ability of *ttfp* to predict closure rates is greater than *sttfp*; which implies that *ttfp* is a more informative measure of productivity. Formalizing this statement requires a measure of *goodness of fit.*

The corresponding measure of goodness of fit for this table is the R^2 of the closure variable regressed on a set of ten mutually exclusive dummy variables representing the decile the plant is in: We measured how much of the variation in the (0,1) closure variable is explained by a plant’s decile. Table IV.3 presents the R^2 for each of the different productivity measures for both the full sample and the pre-1988 sample. Note that the R^2 for *ttfp* is the highest and the R^2 for *sttfp* is the lowest . Note that the factor share-based measures of productivity consistently have lower R^2's (*stfp* and *sttfp*) than the corresponding regression-based measures of productivity (*tfp* and *ttfp*) and labor productivity (*lp* and *tlp*). The TVS-based measures of productivity do somewhat better than the value-added based measures (compare *ttfp* to *tfp*, *sttfp* to *stfp*) with the noted exception of labor productivity, which is to be expected because sales per employee ignores the presence of material inputs in the production process. Finally, the pre-1988 sample consistently has a better fit. We could attribute this finding to the problems with measurement of capital following 1987. This interpretation is problematic in that labor productivity, which does not use the capital measure, also performs better in the pre-1988 sample.

Table IV.1: Exit rates for deciles when ranked according to *ttfp*

	full sample		pre-1988	
decile when ranked according to ttfp	exit rate	standard error	exit rate	standard error
1	0.42	0.012	0.44	0.013
2	0.35	0.011	0.36	0.013
3	0.32	0.011	0.32	0.012
4	0.26	0.010	0.25	0.012
5	0.25	0.010	0.25	0.011
6	0.21	0.010	0.21	0.011
7	0.21	0.010	0.21	0.011
8	0.20	0.009	0.20	0.011

9	0.21	0.009	0.21	0.011
10	0.27	0.011	0.28	0.012

Table IV.2: Exit rates for deciles when ranked according to stfp

	full sample		Pre-1988	
decile when ranked according to stfp	exit rate	standard error	exit rate	standard error
1	0.36	0.011	0.37	0.013
2	0.30	0.011	0.30	0.012
3	0.33	0.011	0.33	0.012
4	0.28	0.011	0.28	0.012
5	0.27	0.010	0.28	0.012
6	0.25	0.010	0.25	0.011
7	0.21	0.010	0.22	0.011
8	0.24	0.010	0.23	0.011
9	0.21	0.010	0.22	0.011
10	0.27	0.010	0.27	0.012

Table IV.3: Ability of productivity measures to predict exit rates

measure	R^2 i.e., percent of variation in exit rates explained by the decile groupings.	
	full sample	pre-1988
ttfp	.0244	.0281
tlp	.0151	.0180
sttfp	.0084	.0090
tfp	.0162	.0187
lp	.0155	.0176
stfp	.0103	.0116

IV. The association of productivity measures with the growth of inputs and outputs

In this section, we evaluate productivity measures in terms of how associated they are with growth rates of inputs and outputs. Specifically, we report the extent to which the plants in the top deciles have faster growth rates of value added, employment, and capital stock. Plants that increase in size do so because they are competitive and have profitable operations. Therefore, if a productivity measure is associated with growth rates, then the measure is viewed as providing a signal regarding the underlying competitiveness of the plant. For a model that yields these implications within the context of a competitive industry equilibrium see Dwyer (1995a) .

As with closure rates, we measure growth rates over census year pairs. To measure productivity over the census year pair, we take the average of the values at the beginning and end of the period.[11] The growth rates of real value added, total employment and book value of capital are computed. Growth rates are measured as differences divided by the average:

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[11]**Taking the average over census year pairs is necessary to avoid the phenomenon of regression to the mean; the plants that were measured as highly productive in the beginning of the period are likely to loss some of their advantage, their output to input ratio will fall. Therefore, one expects that output will fall and inputs will rise, which is exactly what happens if one computes Tables VI.1&2 on the basis of the productivity at the beginning of the time interval.**

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There are two interesting ways to look at growth rates: first, we can look at the straight measure, and second, we can look at a plant's growth rate relative to the four-digit industry average. The question is: would we expect a highly productive, broad-cloth woven fiber cotton mill (a declining industry) to the grow fast, or to grow fast for a cotton mill? We computed the results for both measures and they are substantively the same. The results that we present are for growth rates measured as deviations from the four-digit industry mean growth rate.

Table VI.1 presents the mean growth rates of plants by productivity deciles where the measures are ranked according to *tfp* for the full sample. Note that the more productive plants are creating jobs and producing more output, while the less productive plants are destroying jobs and reducing output. There is not a clear association, however, between productivity and growth of capital stock. Table VI.2 presents that same chart for the factor share measure, value-added productivity (*stfp*). Using this measure, there is still a positive association between productivity of job creation and output growth, only it is much less pronounced.

Further, the more productive plants are actually downsizing in terms of their capital stock. This suggests that the *tfp* measure outperforms the *stfp* measure.

One way of evaluating this statement is to regress growth rates (measured as deviations from the industry mean) onto a set of dummies representing the plant's decile, following the methodology in Section V. Based on this approach, Table VI.2 presents a column stating whether or not the growth rates are increasing in productivity (+, +?, ?, -?, and - denote increasing, increasing but not a clear pattern, no clear pattern, decreasing but not a clear pattern, and decreasing, respectively). In terms of growth of output and employment, *ttfp, tfp,* and *lp* have the largest R^2's, and *sttfp*, *stfp,* and *tlp* performs the worst in terms of goodness of fit. In predicting the growth of book value of capital, *ttfp*, *lp,* and *tlp* are positively associated with growth. For the growth of output and job creation, labor productivity and the regression-based measures of productivity consistently outperform the factor share-based measures of productivity.

Table VI.1: The association of tfp with the growth of inputs and outputs

decile when ranked according to TFP	growth of real value added	growth of employment	growth of book value of capital
1	-0.110 (0.029)	-0.058 (0.018)	0.006 (0.028)
2	-0.042 (0.021)	-0.061 (0.016)	-0.010 (0.026)
3	-0.068 (0.019)	-0.035 (0.015)	-0.006 (0.026)

4	0.024	(0.020)	0.001	(0.015)	0.029	(0.026)
5	-0.011	(0.019)	-0.013	(0.015)	-0.008	(0.027)
6	0.020	(0.018)	0.019	(0.015)	-0.032	(0.027)
7	0.009	(0.018)	0.027	(0.015)	0.010	(0.027)
8	0.085	(0.020)	0.038	(0.016)	0.057	(0.029)
9	0.016	(0.021)	0.034	(0.016)	-0.008	(0.032)
10	0.082	(0.025)	0.049	(0.018)	0.002	(0.033)

Table VI.2: The association of stfp with the growth of inputs and outputs

decile when ranked according to TFP	growth of real value added		growth of employment		growth of book value of capital	
1	-0.073	(0.028)	-0.043	(0.017)	0.068	(0.024)
2	-0.066	(0.021)	-0.047	(0.016)	0.050	(0.024)
3	-0.021	(0.020)	-0.035	(0.015)	0.074	(0.023)
4	0.019	(0.019)	-0.007	(0.015)	0.021	(0.024)
5	0.001	(0.020)	0.000	(0.015)	0.059	(0.023)
6	0.029	(0.018)	0.009	(0.014)	0.019	(0.025)
7	0.021	(0.019)	0.038	(0.015)	0.030	(0.026)
8	0.023	(0.020)	0.033	(0.016)	-0.026	(0.029)
9	0.038	(0.021)	0.048	(0.016)	-0.071	(0.034)
10	0.033	(0.025)	0.005	(0.018)	-0.191	(0.043)

Table V.3 Predictive Power of Productivity Measures

measure	growth of real value added		growth of total employment		growth of book value of capital	
	increasing?	R^2	increasing?	R^2	increasing?	R^2
tfp	+	.0079	+	.0062	?	.0008
stfp	+	.0035	+	.0044	-	.0079
lp	+	.0085	+	.0069	+	.0050
ttfp	+	.0052	+	.0067	+	.0015
sttfp	+	.0032	+?	.0049	-	.0032
tlp	+	.0030	+	.0054	+	.0052

VI. Moving average measures of productivity

Previous research has revealed that a large portion of productivity differentials are transitory; in other words they erode quickly. One would suspect that plants would make their growth and closure decisions on the basis of the persistent (sustainable) component of productivity. Therefore, if we filter out the transitory component by taking a moving average of productivity, we should increase the explanatory power of the measure.

The moving average-based measures of productivity, *MTFP*, *MLP*, *MSTFP*, *MTTFP*, *MTLP*, *MSTTFP*, are computed as follows:

$$MX = exp(0.45x_t + 0.24x_{t-1} + 0.31x_{t-2})$$

where x is the relevant measure of productivity.[12] This procedure should average out transitory shocks. This moving average measure can only be computed for plants that were in the same industry in the previous two years. Creating these measures, therefore, creates a sample selection bias. In order to run productivity races on the moving average measures versus measures of productivity based only on the most recent year of data (hereafter, one-shot measures), we create a new data set that contains only the plants for which a moving average can be constructed. For this new

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[12] This moving average is a forecast of the sustainable component of productivity in the next period. It is based on the methodology presented in Dwyer (1995d), and utilizes the parameter estimates taken from the entire textile industry.

data set, the sample selection criteria is the same across the different productivity measures.

We first asked the question: is the moving average measure of productivity more closely associated with future measures of productivity and profits? Table V.1 presents rank correlation coefficients between the one-shot measures of productivity and the moving average measures of productivity with measures of productivity and profits 5 years in the future. The moving average measure is more closely associated with future productivity and profits for all productivity measures except tlp.

Table V.2 presents the goodness of fit for the twelve measures in terms of their ability to predict closure, following the methodology in Section III. The moving average measures only outperform the corresponding one-shot measures for one of the six measures (*lp* vs. *mlp*), which is surprising. Perhaps the weights used in constructing the moving average are the problem. Therefore, we let the data tell us how to weight the three values by estimating a logit model. Tables V.3-V.8 report these results for each of the six measures of productivity. For *tfp*, *stfp*, and *lp*, plants appear to be closing on the basis of both the current year's and last year's productivity (their coefficients are significant and negative, while the coefficient on the two year lag is small and insignificant). For *ttfp*, *sttfp*, and *tlp*, in contrast, plants appear to be closing on the basis of three years of data on productivity, but the coefficient on the two year lag is significant and positive. This counter-intuitive finding is more likely to be a statistical artifact rather than being of economic interest. By a large, the evidence supports that averaging productivity over time yields a better measure of productivity than only looking at productivity in one given year.

Table V.1: Rank correlations between productivity, average productivity, future productivity and future profits.

	tfp_t	$mtfp_t$	tfp_{t+5}	$mtfp_{t+5}$	$Prof/Va_{t+5}$	$Prof/TE_{t+5}$	$Prof/Sales_{t+5}$	$Prof/Capital_{t+5}$
tfp_t	1.000	0.846	0.389	0.483	0.306	0.324	0.218	0.247
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$mtfp_t$	0.846	1.000	0.401	0.504	0.321	0.340	0.244	0.256
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	$stfp_t$	$mstfp_t$	$stfp_{t+5}$	$mstfp_{t+5}$				
$stfp_t$	1.000	0.854	0.335	0.467	0.245	0.250	0.193	0.278
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$mstfp_t$	0.854	1.000	0.349	0.476	0.258	0.262	0.219	0.288
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	lp_t	mlp_t	lp_{t+5}	mlp_{t+5}				
lp_t	1.000	0.858	0.452	0.526	0.331	0.358	0.225	0.211
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
mlp_t	0.858	1.000	0.468	0.550	0.345	0.376	0.248	0.219
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	$ttfp_t$	$mttfp_t$	$ttfp_{t+5}$	$mttfp_{t+5}$				
$ttfp_t$	1.000	0.833	0.446	0.559	0.281	0.295	0.183	0.214
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$mttfp_t$	0.833	1.000	0.461	0.566	0.307	0.311	0.199	0.226
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	$sttfp_t$	$msttfp_t$	$sttfp_{t+5}$	$msttfp_{t+5}$				
$sttfp_t$	1.000	0.834	0.373	0.515	0.216	0.221	0.202	0.243
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$msttfp_t$	0.834	1.000	0.398	0.523	0.239	0.232	0.221	0.256
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	tlp_t	$mtlp_t$	tlp_{t+5}	$mtlp_{t+5}$				
tlp_t	1.000	0.937	0.712	0.786	0.299	0.314	0.033	0.130
	0.000	0.000	0.000	0.000	0.000	0.000	0.133	0.000
$mtlp_t$	0.937	1.000	0.714	0.784	0.297	0.318	0.033	0.126
	0.000	0.000	0.000	0.000	0.000	0.000	0.141	0.000

Table V.2 Ability of productivity measures to predict closure rates vs. moving average-based measures

measure	full Sample	pre-1988
TFP	.0211	.0257
MTFP	.0211	.0219
LP	.0236	.0244
MLP	.0255	.0257
STFP	.0174	.0231
MSTFP	.0140	.0182
TTFP	.0241	.0280
MTTFP	.0213	.0210
TLP	.027	.0298
MTLP	.024	.0225
STTFP	.0157	.0218
MSTTFP	.0126	.0133

Table V.3: Logit of exit regressed onto a lag structure of tfp

No of Obs: 4584				
Criterion	Intercept	Intercept and Covariates	c^2 for 3 degrees of freedom	
-2logL	4425.737	4345.908	79.829	(p=0.0001)
Score	.	.	81.882	(p=0.0001)
Variable	parameter estimate	standard error	Pr>0	Standardized Estimate
intercept	-1.4957	0.0388	0.0001	.
tfp	-0.3965	0.0704	0.0001	-0.127976
tfp_{t-1}	-0.2583	0.0753	0.0006	-0.084794
tfp_{t-2}	-0.00681	0.0759	0.9285	-0.002261

Table V.4: Logit of exit regressed onto a lag structure of stfp

No of Obs: 4584				
Criterion	Intercept	Intercept and Covariates	c^2 for 3 degrees of freedom	
-2logL	4425.737	4391.884	33.854	(p=0.0001)
Score	.	.	34.405	(p=0.0001)
Variable	parameter estimate	standard error	Pr>0	Standardized Estimate
intercept	-1.4983	0.0393	0.0001	.
stfp	-0.1917	0.0645	0.0029	-0.067877
$stfp_{t-1}$	-0.2037	0.0725	0.005	-0.070331
$stfp_{t-2}$	-0.0111	0.0725	0.8781	-0.003874

Table V.5: Logit of exit regressed onto a lag structure of lp

No. of Obs: 4588				
Criterion	Intercept	Intercept and Covariates	c^2 for 3 degrees of freedom	
-2logL	4430.33	4330.452	99.879	(p=0.0001)
Score	.	.	101.516	(p=0.0001)
Variable	parameter estimate	standard error	Pr>0	Standardized Estimate
intercept	-1.473	0.0386	0.0001	.
lp	-0.4627	0.071	0.0001	-0.155073
lp_{t-1}	-0.2627	0.0762	0.0006	-0.089383
lp_{t-2}	0.032	0.0768	0.6772	0.010966

Table V.6: Logit of exit regressed onto a lag structure of ttfp

No of Obs: 4534				
Criterion	Intercept	Intercept and Covariates	c^2 for 3 degrees of freedom	
-2logL	4346.171	4270.519	75.652	(p=0.0001)
Score	.	.	71.194	(p=0.0001)
Variable	parameter estimate	standard error	Pr>0	Standardized Estimate
intercept	-1.5033	0.0391	0.0001	.
ttfp	-1.1989	0.1869	0.0001	-0.184698
$ttfp_{t-1}$	-0.4682	0.218	0.0318	-0.072354
$ttfp_{t-2}$	0.5594	0.1975	0.0046	0.087729

Table V.7: Logit of exit regressed onto a lag structure of sttfp

No of Obs: 4534				
Criterion	Intercept	Intercept and Covariates	c^2 for 3 degrees of freedom	
-2logL	4346.171	4281.019	65.152	with 3DF
Score	.	.	64.157	with 3DF
Variable	parameter estimate	standard error	Pr>0	Standardized Estimate
intercept	-1.5861	0.0423	0.0001	.
sttfp	-1.1145	0.1596	0.0001	-0.195239

$sttfp_{t-1}$	-0.1488	0.205	0.4681	-0.0253
$sttfp_{t-2}$	0.5825	0.1883	0.002	0.099418

Table V.8: Logit of exit regressed onto a lag structure of tlp

No of Obs: 4588				
Criterion	Intercept	Intercept and Covariates	c^2 for 3 degrees of freedom	
-2logL	4430.33	4346.093	84.238	with 3DF
Score	.	.	83.337	with 3DF
Variable	parameter estimate	standard error	Pr>0	Standardized Estimate
intercept	-1.4568	0.0389	0.0001	.
tlp	-0.3345	0.1118	0.0028	-0.109777
tlp_{t-1}	-0.7056	0.149	0.0001	-0.229999
tlp_{t-2}	0.5271	0.1344	0.0001	0.171964

VII. Conclusion

This paper has shown that measures of plant-level productivity are indicative of a plant's competitive position. Plant-level productivity is positively associated with growth of output, job creation, and increased capital usage. The most productive plants are the least likely to close, and the most productive plants are the most profitable. With the exception of profits, the productivity measures explain only a small amount of the variation in performance.

Of the different measures, value added per employee and the regression-based measures of productivity (*TTFP* and *TFP*) consistently outperform the factor share-based measures of productivity in terms of explaining variation in performance.

Moving average measures of productivity, which were intended as a means of filtering out transitory measurement error, appear to outperform the measures of productivity that are based only one year of data. They are more closely associated with future profits and productivity. Further, exit decisions by plants appear to be based on the productivity measures in several different time periods.

The fact that the measures of productivity that place the largest weight on capital (factor share measures) are consistently outperformed by the other measures suggests that measurement error in a plant's capital stock may be problematic. Therefore, part II of this paper will experiment with different measures of capital to try to minimize this problem.

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Appendix: Data

Our data set consists of the textile plants (SIC 2200-2299) in the Longitudinal Research Database (LRD), which is based on the Annual Survey of Manufactures (ASM) and the Census of Manufactures (CM).[13] The panel runs from 1972 until 1992. Regression analysis can be performed separately on 22 different industries. Statistics taken from industries 2259 and 2296 are sometimes suppressed due to confidentiality requirements.

The CM is conducted every five years (1967, 1972, 1977, 1982, 1987, and 1992) and each plant is, in principle, sampled with a probability of one. The ASM draws a sample of plants two years after the CM and follows this sample for five years (these samples begin in 1974, 1979, 1984, and 1989). It adds newly created plants to the sample every survey year. The sample probability increases with plant size, and it becomes one for plants with more than 250 employees.

Our sample is a subset of a sample that includes all information available on every plant ever in the SIC codes 2200-2299 from 1967 to 1989. The sample is truncated to drop administrative record cases, which are small plants for which only a limited amount of information is collected, and drops pre-1972 data. The pre-1972 observations were dropped in order to construct a complete annual time series. The

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[13]For a detailed description of this database see McGuckin and Pascoe (1988).

unbalanced sample contains five years in which all firms are sampled with a probability of one (in theory), and four different samples in which large firms are sampled with a higher probability than are smaller ones.

The relevant price indices were taken from the National Bureau of Economic Research (NBER) productivity database (Gray, 1989), which are at the four-digit level. The 1992 values were set to equal the 1991 values, because the prices indices for 1992 were not yet available.

To resolve an apparent inconsistency in the classification of plants in census and non-census years the following aggregations are made: SIC 2258 includes Derived Industry Code (DIND) 2258 and 2292; SIC 2273 includes DIND 2271, 2272, and 2279; SIC 2283 includes DIND 2281, 2283, and 2284; SIC 2299 includes DIND 2291, 2293, 2294, and 2299. The relevant price indices were computed as a Laspeyres price index with 1987 as a base year, using NBER's productivity database with total value of shipments as the relevant weights (Gray, 1989).

Variable Construction:

RVA (Real value added)

Value added is computed as total value of ships (TVS) less the cost of materials (including materials, supplies, fuel, electric energy, cost of resales, and cost of contract work). Value added is deflated through Gray's shipments price index to generate RVA.

RTVS (Real total value of shipments)

RTVS is computed as TVS plus changes in the value of inventories, deflated by the industries' four-digit investment price index.

TE (Total employment)

Total employment is the sum of the average number of production workers and nonproduction workers.

BOOK (Gross book value of capital)

The only measure of assets that can be calculated consistently across small plants and large plants is gross book value. BOOK is the gross book value of buildings and machinery at the end of the period plus the capitalized value of rental payments deflated by a four-digit investment price index.

$$BOOK_t = (BAE_t + MAE_t)/PINV_t + (BR_t+MR_t)/(r_tPINV_t).$$

Here BAE and MAE are the gross book value of assets and machinery at the end of the period; BR and MR are rents paid for buildings and machinery, and r is the user cost of capital (Wang, 1994). The gross book value is equal to the gross book value in the previous period plus new investment less retirements. Unfortunately, in 1986 and 1988-1991, the U.S.

Census stopped collecting information on retirements. Therefore, during these time periods the book value of capital is computed as the previous period’s book value plus the level of investments. This paper documents that the lack of information on retirements increases the amount of measurement error in the data.

Payroll and Average Wages

Payroll is the sum of total salaries and wages (SW) plus legally required supplemental labor costs (LE) and voluntary supplemental labor costs (VLC). Average wages are payroll divided by total employment (TE).

Materials

Materials is the cost of materials divided by a four-digit materials price index.