COMPUTER NETWORKS AND PRODUCTIVITY REVISITED:

DOES PLANT SIZE MATTER?

EVIDENCE AND IMPLICATIONS

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Abstract

Numerous studies have documented a positive association between information technology (IT) investments and business- and establishment-level productivity, but these studies usually pay sole or disproportionate attention to small- or medium-sized entities. In this paper, we revisit the evidence for manufacturing plants presented in Atrostic and Nguyen (2005) and show that the positive relationship between computer networks and labor productivity is only found among small- and medium-sized plants. Indeed, for larger plants the relationship is negative, and employment-weighted estimates indicate computer networks have a negative relationship with the productivity of employees, on average. These findings indicate that computer network investments may have an ambiguous relationship with aggregate labor productivity growth.

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I. INTRODUCTION

During the last decade, an increasing number of empirical studies have documented the relationship between information technology (IT) and economic performance. Most of these studies find that IT investments are a significant source of additional productivity. For example, Jorgensen and Stiroh (2000), Jorgenson (2001), Stiroh (2002) and Triplet and Bosworth (2002) use industry-level data to demonstrate that IT plays an important role during the surge of productivity growth in the U.S. economy in the late 1990s.

At the firm- and establishment-level, IT investments have also been associated with productivity increases. In a study of large firms, Brynjolfsson and Hitt (2003) find large productivity returns to computer investments over a five-year time horizon. Using panel data for the manufacturing industry, Dunne et. al. (2004) document that increases in computer investment are associated with increases in the dispersion of plant-level wages and productivity. Shin (2006) analyzes the relationship between software usage and productivity on a sample of 525 small to medium size firms, and finds that productivity enhanced in both manufacturing and service firms. Atrostic and Nguyen (2005, 2007) and Atrostic, Motohashi and Nguyen (2008) use plant-level data to study the relationship between computer network use and the labor productivity of manufacturing plants, and find that computer networks are associated with higher productivity.

Less attention has been devoted to the role of business size in the effect of IT investments on productivity. Some papers provide a discussion of mechanisms by which IT may be associated with higher productivity without explicitly mentioning the term. For example, Brynjolfsson et. al. (1994), assert that higher IT investments will lower "coordination costs" within and between firms that would lead to smaller, more specialized firms. Similarly, Iansiti et. al. (2005), discussing their sample of firms that employ between 100 and 500 employees, suggest

that in larger firms, successful implementation of an IT infrastructure may be hindered by conflicts between the business units dedicated to IT and other units within a business. The implication of both mechanisms is that productivity returns to the implementation of an IT solution may be greater for small entities than large ones. In this study, we offer evidence that a particular IT investment, a computer network, is associated with higher productivity for smaller business establishments (specifically, manufacturing plants) but not larger ones.

The purpose of this paper is to revisit the apparently strong, positive relationship between computer networks and labor productivity found in Atrostic and Nguyen (2005), and document how this relationship differs for establishments of different sizes. Following Atrostic and Nguyen (2005) we use data taken from the 1999 Computer Network Use Supplement to the Annual Survey of Manufactures (ASM) linked to data in 1997 and 1992 Census of Manufactures (CM). We document that the relationship between computer networks is strongly positive for the more numerous small- to medium-sized establishments in this dataset, but is strongly negative for larger plants. These very different computer network productivity differentials have serious implications for how to interpret the previous finding that a computer network is associated with 5% higher plant-level productivity. In this study, we argue that the Atrostic and Nguyen (2005) regression specification, in which all plants are given equal weight, recovers the productivity difference associated with the presence of a computer network for the *typical plant*, but it does not represent the association for the *typical worker*, or the economy as a whole.

We give critical consideration to the implications of different weights that can be applied to plant-level regression specifications. Weighting all plants equally produces regression estimates that represent the relationship between computer networks and productivity that exists for the much more numerous smaller plants. However, large plants, by definition, constitute a

share of aggregate labor productivity that is proportionate to their size. In order to recover the impact of computer networks on aggregate labor productivity, we estimate regression models in which plants are weighted by total employment. In order to do so, we construct weights that are appropriate to the ASM, which over-samples larger plants. We find that the employment-weighted estimates indicate a substantially different relationship between computer networks and labor productivity: estimates from the weighted regressions indicate a strongly negative association rather than strongly positive one.

We would like to caution readers that, in the 1999 ASM, nearly 90% of sampled plants have a computer network. However, of the largest plants, 97% report operating a computer network. In order to provide an additional empirical reference point in the presence of different levels of adoption of this technology among establishments of different sizes, we estimate regression specifications similar to those in Atrostic and Nguyen (2005) separately for three broad size categories. However, this disaggregation of our results does not overcome the fundamental difficulty of conducting our empirical analysis using the 1999 ASM, which is that, by 1999, most manufacturing plants had adopted computer networks. Therefore, the cross-sectional differences in our sample of plants may not represent productivity differentials that are implicit in studies of longer time periods, such as the national accounts estimates in Jorgenson (2001) or manufacturing plant-level estimates in Dunne et. al. (2004).

The paper proceeds as follows. In the next section, we describe our data and variables. Section III presents the empirical model and estimation method. We present the empirical results in section IV. Section V concludes the paper.

II. DATA SOURCES AND VARIABLE CONSTRUCTION

Data and Sources

The Computer Network Use Supplement to the 1999 ASM provides the first large-scale picture of the prevalence and use of computer networks in U.S. manufacturing. We link data from the Supplement to the 1999 ASM data and the 1992 and 1997 CM in order to obtain data for our empirical analysis. The Supplement originally contains 39,056 plants of which 30,313 merge with the 1992 and 1997 CM and have all values of the key variables in the estimation of labor productivity, total employment and total value of shipments, greater than zero. Deleting observations with total employment less than five and observations with missing values in 1997 and 1999 further reduces the sample to 29,177. Additional removal of any observations with missing values for any other variable in 1992 (to be used in the two-stage regressions) described below yields 27,007 plants.[2]

Variable Construction

Variables in our models are defined as follows. Subscript *t* takes the values *92*, *97* and *99*, which imply source data is from the 1992 and 1997 CM, and the 1999 ASM, respectively.

Labor Productivity (LP_t): Labor productivity is output divided by labor, or Q_t/L_t.

Output (Q_t): A plant's total value of shipments serves as a revenue proxy for output.

Capital (K_t): The book value of a plant's gross capital stock (including buildings and machinery assets) serves as a proxy for capital services. While book values are likely to be

[2] For more details on deriving a sample from these data sources, see Atrostic and Nguyen (2005, 2007). We deleted plants with 4 employees or less because data on these small plants are largely imputed based on administrative records. I our preliminary work, we included plants with less than 5 employees and found similar results.

subject to measurement error, this approach is well established and is used in, for example, McGuckin et al. (1998), Greenan et al. (2001), Atrostic and Nguyen (2005).

Labor (L_t): The labor input is the total number of employees working at the plant.[3]

Materials (M_t): The materials input is the sum of values of materials, parts, energy and contract work. Expenditures on materials is an important control variable when estimating the relationship between computer networks on productivity because it permits comparison between plants that have an in-house IT department and those who outsource their IT services. Outsourcing plants may have a lower number of individuals that are included in payroll and, therefore, raw labor productivity will increase. However, these same plants will have a higher materials expenditure to labor ratio. This control variable accounts for what might otherwise cause omitted variables bias in our regression specifications.

Computer Network ($Network_{99}$): This variable takes on a value of 1 if the plant's response to the Computer Network Use Supplement indicated any kind of computer network, and 0 otherwise. The Supplement allowed respondents to report operating an internet, intranet, Local Area Network, Electronic Data Interchange, Extranet, or an "other" computer network.

Multi-unit firms' plants ($MULTI_t$): This variable takes on the value of 1 if the plant is part of a multi-unit firm, and equals 0 otherwise.

Industries (IND_t): We construct two different sets of dummy variables for 3-digit NAICS industries for 1999 and 1997 and 2-digit SIC industries in 1992.

[3] We also used hours worked instead of total employment and obtained similar results. In keeping with Atrostic and Nguyen (2005), we use total number of employees as a proxy for labor.

Relative labor Productivity (RLP_t): This variable is the plant's labor productivity divided by its industry-average labor productivity, measured at the 3-digit NAICS from 1997 CM and 2-digit SIC from the 1992 CM.

Computer Expenditures ($COMP_{92}$). This variable is defined as the computer expenditure of the plant divided by total number of employees in the 1992 CM.

$SKILL_t$: We use the number of non-production workers divided by total number of employees in the plant as a proxy for skill.

$SIZE_{99}$: When estimating the equations using all observations, we define six size classes based on total employment in the 1999 ASM, L_{99}:

- $SIZE_{99,1}$ =1 if $5 \leq L_{99} < 50$, $SIZE_{99,1} = 0$, otherwise
- $SIZE_{99,2} = 1$ if $50 \leq L_{99} < 100$, $SIZE_{99,2} = 0$, otherwise
- $SIZE_{99,3} = 1$ if $100 \leq L_{99} < 250$, $SIZE_{99,3} = 0$, otherwise
- $SIZE_{99,4} = 1$ if $250 \leq L_{99} < 500$, $SIZE_{99,4} = 0$, otherwise
- $SIZE_{99,5} = 1$ if $500 \leq L_{99} < 1000$, $SIZE_{99,5} = 0$, otherwise
- $SIZE_{99,6}$ =1 if $L_{99} \geq 1000$, $SIZE_{99,6} = 0$, otherwise.

Small, Medium and Large: In some estimates, we split our data into 3 size classes and estimate separate regressions, as follows:

- *Small*: $5 \leq L_{99} < 100$ employees
- *Medium*: $100 \leq L_{99} < 250$ employees
- *Large*: $L_{99} \geq 250$ employees.

We emphasize that it is impossible to offer universally accepted definitions for small, medium and large plants, and that the terms should be viewed as relative. However, our results are not particularly sensitive to the values used to define the categories.

Weight: We calculate an "employment weight" as the 1999 ASM sample weight (not adjusted for non-response) multiplied by total employment. The meaning and proper interpretation of this weight are discussed further in the next section.

III. THE EMPIRICAL MODEL AND ESTIMATION METHOD

The Empirical Model

Following Atrostic and Nguyen (2005), we specify a three-factor Cobb-Douglas production function, extended to incorporate plant characteristics as control variables, and estimate log-labor productivity with corresponding marginal effects as:

$$\begin{aligned} \text{Log}(Q_{99}/L_{99}) = {} & \beta_0 + \beta_1 Network_{99} + \alpha_1 \log(K_{97}/L_{97}) + \alpha_3 \log(M_{99}/L_{99}) + \\ & + \alpha_5 \log(SKILL_{99}) + \alpha_6 MULTI_{99} + \alpha_7 \log(RLP_{97}) + \sum \gamma_j IND_{99,,j} \\ & + \sum \lambda_s \, SIZE_{99,s} + \varepsilon \end{aligned} \tag{1}$$

where the variables are as described above with corresponding marginal effects and ε is an error term. We estimate equation (1) alone using Ordinary Least Squares.

Note that the empirical specifications in this paper differ from that in Atrostic and Nguyen (2005), who measure size as a continuous variable, using total employment. Since we focus on the productivity differentials for plants of different sizes, we incorporate categorical

variables for size. Another advantage of this approach over the use of total employment as a right-hand variable is to avoid potential bias from measurement error.[4]

As Atrostic and Nguyen (2005) point out, the estimated coefficient for the *Network99* variable equation (1) is most likely subject to endogeneity bias. Thus, following Atrostic and Nguyen (2005) we employ a two-step specification in which the presence of a computer network is related to its past characteristics according to the following probit regression:

$$Pr(Network_{99}) = \Phi(\gamma_0 + \gamma_1 \log(RLP_{92}) + \gamma_2 \log(K_{92}/L_{92}) + \gamma_3 \log(SKILL_{92})$$

$$+ \gamma_4 \log(COMP_{92}) + \gamma_5 MULTI_{92} + \Sigma \varphi_j IND_{92,j}) \qquad (2)$$

where variables are as described above with corresponding marginal effects.

We first estimate equation (2) and use its parameter estimates to construct an instrumental variable, the estimated probability of a plant having a computer network, and use this in the estimation of equation (1) to account for possible endogeneity bias associated with the $Network_{99}$ variable. Specifically, $Pr(Network_{99}) = \Omega(-Networkhat)$, where Ω is the cumulative density function for the standard normal variable and *Networkhat* is the fitted value of $Network_{99}$. To do so, we apply Stata's treatreg procedure with robust standard errors.

Weights and Size Categories

We estimate both weighted and un-weighted versions of our Ordinary Least Squares and two-stage estimation strategies described above. Note that an "un-weighted" empirical specification implicitly assigns a uniform weight to all observations. Our weighted specifications use employer size to recover the aggregate relationship between computer networks and

[4] We note, however, that using the size variables does not significantly affect the estimated coefficient of the Network variable.

productivity. If the computer network differential is similar for both small and large plants, this weight will not alter the point estimate associated with the computer network variable. Because our empirical evidence suggests differences by plant size, any single summary statistic for the "average" association between computer networks and labor productivity will need to weight by total employment. It proved necessary to use ASM sample weights to adjust the total employment weight because plants are sampled for the 1999 ASM with greater probability as they increase in size, with plants of greater than 250 employees being sampled with certainty. Weighting by total employment alone under-represents the employment of smaller plants, and this correction affects the weighted estimates that we report in this paper.

Note that we estimated two additional sets of empirical specifications, but do not report the results in this paper. One specification weighted the Atrostic and Nguyen (2005) regressions by ASM sample weights. This provides appropriate weights to smaller plants sampled with lower probability in the ASM. However, because the productivity differential is so similar among small plants, estimates that weight by the ASM sample weights are nearly identical[5] to unweighted estimates, and so we do not report them. Furthermore, we estimated regression models in which plants are weighted by total employment, without an ASM correction. This specification produces empirical estimates of the association between computer networks and productivity that were also negative and sometimes more than twice the magnitude of employment-weighted estimates that employ the ASM correction. These larger negative estimates do not have a straightfoward interpretation, so we omit results that use unadjusted employment weights as well.

[5] For example, the Ordinary Least Squares estimation of equation (1) yields a point estimate of .0433 of the cofficient on the presence of a computer network after a simple application of the ASM sample weights, rather than the unweighted .0446 which we report in Table 2, rounded to three significant digits.

To summarize, in the following section we report results for the two weighting methods that best describe the patterns in the sample under consideration: "un-weighted" regressions refer to ASM-based regressions that weight all respondents equally, as in Atrostic and Nguyen (2005), and "weighted" or "employment-weighted" results refer to those specification in which the weight is calculated as total employment multiplied by the ASM sample weight.

In order to provide an additional empirical reference point, we estimate regression specifications similar to those in Atrostic and Nguyen (2005) separately for plants we categorize as *Small* (5-99 employees), *Medium* (100-249) and *Large* (250+), to obtain the relationship between computer networks and productivity for each size class. These regression specifications may prove informative to readers who, in light of later evidence that we present on the presence of different levels of adoption of this technology among establishments of different sizes, and the heterogeneous relationship between computer networks and productivity, do not find the estimation of an average association between computer networks and productivity meaningful.

IV. EMPIRICAL RESULTS

Table 1 shows average plant productivity and employment by whether or not the plant has a computer network, disaggregated by size and whether the firm that operates the plant is multi-unit or not. Employment characteristics are as follows. The average employment per plant is 237 employees. Among these plants, 45.24 percent are small plants (<100 employees), 29.23 percent are medium plants (100-249 employees), and 25.53 percent are large plants (250+ employees). The average employment for small, medium and large plants are 46.8, 161.6, and 661.4 workers, respectively. While small and medium plants account for 74.5 percent of the total

number of plants in the sample, they employ only 29 percent of total employment. In contrast, "large" plants account for only 25 percent of total plants, but employ 71.0 percent of total employment. Note that while our sample includes less than 10 percent of 350,000 establishments in the U.S. manufacturing sector, it accounts for more than 40 percent of all manufacturing employment in the U.S. because the ASM over-samples large plants.

These descriptive statistics indicate that computer networks are associated with higher productivity among smaller plants, and lower productivity among larger plants. Note that there are different degrees of computer network penetration by size. While 10.4 percent of all plants do not have a computer network, 18 percent of *Small* plants, 5 percent of *Medium* plants, and only 3 percent of *Large* plants do not have a computer network. Among plants with fewer than 250 employees, labor productivity is approximately 25% higher among plants with a computer network, indicating a strong, positive relationship between the presence of a computer network and productivity. However, the productivity differential is clearly negative among larger plants. Based on simple averages, the largest plants with a computer network are roughly 25% less productive than those that do not operate a computer network. Regression adjustment reduces the magnitude of the productivity differences, but not their direction.

Our regression results using all 29,262 observations (for OLS) and 27,007 observations (for two-stage regressions) are shown in Table 2.[6] The un-weighted OLS and two-stage estimates show that computer networks are associated with higher labor productivity, while employment-weighted estimates both indicate a strong, negative relationship. All estimates of the coefficient on the computer network variable are statistically significant at the 1 percent level. The positive

[6] The sample reduced to 27,007 observations due to missing values in 1992 for certain variables such as $COMP_{92}$ (computer investment in 1992) and $SKILL_{92}$ (non-production workers/total employment ratio).

estimates obtained from un-weighted regressions confirm the Atrostic and Nguyen (2005) finding that computer networks are associated significantly higher productivity among plants. Note that un-weighted regressions assign equal weight to every plant and small and medium plants dominate the sample. When weighted by employment, the association is significantly negative, indicating that computer networks have a strong negative relationship with the typical worker exposed to them.

Table 3 shows the regression results by our three broad size categories. It is clear that the effect of computer networks on productivity is positive and significant for plants in our *Small* and *Medium* categories. However, for larger plants in our *Large* category, which have 250 or more employees, computer networks are clearly associated with lower productivity, and this relationship is robust to both control for observable characteristics and our two-stage approach. Specifically, OLS results show that computer networks are associated with a 4.6 percent increase in labor productivity for *Small* plants and 7.6 percent increase for *Medium* plants. However, computer networks are associated with a 6.4 percent decline in labor productivity among the set of largest plants.

The two-stage regression results in Tables 2 and 3 are similar in sign to those obtained from OLS regression, but their interpretation is less straightforward. This is because the variable $Network_{99}$ in the OLS regression is a dummy variable whose value is either 0 or 1, whereas the $\Pr(Network_{99})$ variable in the two-stage regressions is continuous and has value between 0 and 1. Therefore, following Atrostic and Nguyen (2005), we compare the effects of computer network on plant productivity at two points in the predicted productivity having a computer network. These comparisons are reported in Table 4. The percentage productivity increase (or decrease) is

calculated by multiplying the difference in the predicted probability of having a computer network by the estimated coefficient of the Pr(*Network)* variable. For example, a *Small* plant at the 99th percentile of the probability distribution (0.9805) enjoys a labor productivity that is higher than that in the plant at the 1st percentile (0.5049) in the predicted probability distribution by 21.06 percent (= (0.9805 – 0.5049) x 0.443). Since 18 percent of *Small* plants in our working sample do not have a computer network, we compare a plant at the 18th percentile (likely not having a computer network) to a plant at the 99th percentile of the probability distribution (most likely to have a computer network). We find that computer networks are associated with 10.06 percent higher labor productivity in *Small* plants. For *Medium* plants, only 5 percent do not have a computer network. Comparing a *Medium* plant at the 5th percentile to its counterpart at the 99th percentile in the probability distribution, we find that the association between computer networks and labor productivity among medium plants is 3.65 percent. Finally, comparing a *Large* plant at the 3rd percentile and its counterpart at the 99th percentile in the productivity distribution, we find that the productivity difference is -3.67 percent.

V. DISCUSSION AND CONCLUDING REMARKS

The empirical phenomenon that establishments with computer networks exhibit higher labor productivity, presented in Atrostic and Nguyen (2005), is entirely due to small- and medium-sized establishments. Larger plants that employ 250 or more employees but lack a computer network exhibit higher productivity than similar large plants with a computer network. Regression specifications that weight all plants equally indicate a positive relationship between the presence of a computer network and productivity, while employment-weighted regressions indicate a negative relationship. This indicates that although the *typical plant* exhibits an

increase in labor productivity in the presence of a computer network, the *typical worker* exhibits lower productivity in the presence of a computer network.

This apparent negative employment-weighted effect of computer network suggests that empirical evidence on the effect of computer networks on small- to medium-sized manufacturing establishments has limited ability to explain aggregate trends in economic growth. For example, Stiroh (2002) notes that IT-intensive industries have grown at a 1% faster rate than industries that use IT less intensively. Jorgenson (2001) furthermore argues that information technology during the early 1990s accounts for roughly 0.5% percent of GDP growth and around 1% of GDP growth in later years. Considering point estimates in Atrostic and Nguyen (2005), which indicate that the adoption computer networks adds around 5% to manufacturing plants' productivity. This implies that the near-universal (90%) adoption of computer networks by the manufacturing industry in 1999 would contribute roughly 15% to US Gross Domestic Product, and may explain a non-trivial portion of such overall gains. However, the micro-level gains from computer networks seem only to represent the effects of computer networks at smaller plants, and when considering aggregate output, these gains are outweighed by a negative relationship among a relatively small number of large plants.

Our results demonstrate the importance of considering sample weights when conducting establishment-level efficiency analyses. Un-weighted regressions give establishments that employ few people as much influence on the parameter estimates as larger plants. Regression specifications that measure the relationship between computer networks and labor productivity, even those that include control variables for establishment size, show a positive relationship. Assigning establishments weights commensurate with establishment size highlights the negative relationship between computer networks and labor productivity, and, therefore, represents

aggregate relationships more clearly. While we do not want to discourage un-weighted regression specifications, we hope that this study highlights the danger of using un-weighted establishment-level estimates to explain economy-wide trends.

We would like to point out the greatest limitation of our results is the fact that the negative effect of computer networks on productivity is driven by a relatively small number (3%) of large employers. This limitation is inherent to the measure of IT intensity employed, and may be able to be overcome using different data that permits IT investments to be captured with a continuous rather than a binary variable. Another potential concern is whether large, productive plants may have become smaller due to the presence of a computer network. There is some evidence that manufacturing plants employ fewer people when they utilize IT more intensively. For example, Brynjlofsson et. al. (1994) show that IT investment leads to a shift in the firm size distribution in favor of smaller firms. Similarly, Bardhan, Whitaker and Mithas (2006), using CM data and a supplemental survey, find that information technology investments are positively associated with outsourcing decisions, allowing estabishment sizes to decrease.

We would like this paper to serve as a reference point in how to interpret the computer network productivity differential. An increasing number of studies note positive effects of computer networks on business outcomes, and discussion of differential effects generally considers which point estimate is the "most positive." We have found using data that produces the "standard" result of IT investments on productivity, that weighting by employment actually produces a negative effect. This may be because small establishments outsource their computer network rather than having an in-house IT department, or there could be some ability for small establishments to increase productivity based on the fact that the information managed by the computer network is shared among fewer individuals. We hope that future studies can re-assess

this productivity differential to see whether it holds more generally, and, if it does, attempt to provide a mechanism by which it occurs.

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Table 1. Plant Labor Productivity by Size

(Numbers in brackets are standard errors and the numbers in parentheses are numbers of establishments)

	With Network		No Network		All plants	
	Productivity	Employment	Productivity	Employment	Productivity	Employment
Size 1	266.6[3.81] (5972)	28.2 [0.16] (5972)	200.7[5.12] (1834)	251.1[3.17] (1834)	251.1[3.17] (7806)	27.0[0.14] (7806)
Size 2	255.2[3.46] (5273)	75.5[0.20] (5272)	192.4[6.67] (634)	68.9[0.54] (634)	248.5[3.18] (5907)	73.0[0.19] (5907)
Size 3	249.7[2.38] (8409)	161.2[0.47] (8409)	201.0 [8.93] (451)	151.6 [1.90] (451)	247.3[2.30] (8860)	160.7 [0.45] (8860)
Size 4	244.2 [3.37] (4379)	350.4 [1.06] (4379)	184.2[10.28] (118)	341.6[6.44] (118)	242.7 [3.30] (4497)	350.2 [1.04] (4497)
Size 5	251.3 [4.72] (2167)	677.8 [2.96] (2167)	290.3 [36.9] (69)	658.9 [14.9] (69)	252.5 [4.71] (2236)	677.2 [2.91] (2236)
Size 6	316.7 [9.06] (962)	1960.9[48.8] (962)	466.6 [60.5] (45)	3201.5[379.3] (45)	323.4 [9.11] (1007)	2016.4[50.2] (1007)
Small	261.3 [2.6] (11245)	49.5 [0.25] (11245)	198.6[4.17] (2468)	34.6 [0.48] (2468)	249.9 [2.27] (13713)	46.8 [0.23] (13713)
Medium	249.7 [2.38] (8409)	161.2 [0.47] (8409)	201.1 [8.93] (451)	151.6 [1.90] (451)	247.3 [2.30] (8860)	161.6 [1.90] (8860)
Large	255.6 [2.67] (7508)	651.3 [8.74] (7508)	270.5 [18.1] (232)	990.7 [102.6] (232)	256.0 [2.65] (7740)	661.4 [9.04] (7740)
SU	157.6 [1.47] (8102)	97.8 [5.13] (8102)	148.7 [3.29] (1867)	44.2 [1.31] (1867)	155.9 [1.34] (9,969)	87.8 [1.28] (9969)
MU	298.0 [1.96] (19060)	315.3 [3.93] (19060)	285.0 [7.35] (1284)	234.5 [21.0] (1284)	297.0 [2.00] (20344)	310.2 [3.92] (20344)
All plants	256.1 [1.35] (27162)	250.4 [2.86] (27162)	204.2 [3.76] (3151)	250.4 [1.50] (3151)	250.7 [1.40] (30313)	237.0 [2.73] (30313)

Table 2. Regression Results: All Observations

Dependent Variable: Plant Log-Labor Productivity
(t-statistics in parentheses)

	OLS Regression		Two-Stage Regressions	
	Un-weighted	Weighted	Un-weighted	Weighted
Intercept	2.781**	2.808**	2.688**	3.314**
	(170.33)	(169.11)	(135.41)	(72.69)
Network	0.045**	-0.033**		
	(5.83)	(3.97)	(--)	(--)
Pr(Network)	(--)	(--)	0.310**	-0.616**
			(17.86)	(25.35)
Log(Skill)	0.044**	0.053**	0.044**	0.036**
	(13.15)	(16.24)	(12.50)	(5.09)
Log(KL97)	0.089**	0.093**	0.091**	0.093**
	(40.30)	(42.94)	(39.95)	(15.73)
Log(ML)	0.491**	0.492**	0.488**	0.448**
	(197.67)	(195.78)	(184.37)	(55.18)
Multi	0.124**	0.107**	0.091**	0.151**
	(22.02)	(16.50)	(15.04)	(15.17)
Size2	-0.047**	-0.016+	-0.048**	-0.009
	(7.00)	(1.72)	(6.87)	(0.82)
Size3	-0.079**	-0.028**	-0.078**	-0.017+
	(12.23)	(3.20)	(11.51)	(1.61)
Size4	-0.091**	-0.016+	-0.087**	-0.005
	(11.56)	(1.66)	(10.72)	(0.38)
Size5	-0.082**	-0.005	-0.082**	0.020
	(8.33)	(0.56)	(8.19)	(1.48)
Size6	-0.016	0.098**	-0.014	0.105**
	(1.23)	(9.82)	(1.06)	(5.26)
Industry (3-digit NAICS)	Yes	Yes	Yes	Yes
R^2	0.7375	0.7211	--	--
Numbers of Plants	29,261	29,261	27,007[a]	27007[a]

** denotes "significant at the 1 percent level", * denotes "significant at the 5 percent level", and + denotes "significant at the 10 percent level".

[a] For the difference in the numbers of observations, See footnote 6.

Table 3: Regression Results by Plant Size

Dependent Variable: Plant Log-Labor Productivity
(t-statistics in parentheses)

	Small Plants 4 ≤ TE <100		*Medium Plants* *100 ≤ TE < 250*		Large Plants 250≤ TE	
	OLS	Two-stage	OLS	Two-stage	OLS	Two-stage
Intercept	2.821**	2.788**	2.561**	2.448**	2.853**	3.406**
	(117.46)	(95.35)	(82.21)	(64.87)	(70.20)	(83.31)
Network	0.045**	(--)	0.076**	(--)	-0.063**	(--)
	(4.86)		(4.48)		(2.60)	
Pr(Network)	(--)	0.443**	(--)	0.356**	(--)	-0.667**
		(20.18)		(11.37)		(25.43)
Log(Skill)	0.053**	0.051**	0.025**	0.023**	0.051**	0.044**
	(9.52)	(8.60)	(4.29)	(3.83)	(8.17)	(7.08)
Log(KL97)	0.073**	0.075**	0.096**	0.095**	0.099**	0.099**
	(21.52)	(20.43)	(24.21)	(23.84)	(23.03)	(23.053)
Log(ML)	0.475**	0.461**	0.512**	0.506**	0.498**	0.500**
	(131.25)	(112.63)	(110.61)	(105.98)	(93.67)	(93.93)
Multi	0.148**	0.108**	0.088**	0.083**	0.111**	0.116**
	(18.52)	(12.08)	(9.51)	(8.66)	(2.60)	(6.94)
Industry (3-digit NAICS)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.7547	--	0.7442	--	0.6924	--
Numbers of Plants	12,887	11,117	8,726	8,400	7,648	7,490

** denotes "significant at the 1 percent level", * denotes "significant at the 5 percent level", and + denotes "significant at the 10 percent level".

Table 4. Two-Stage Estimates by Percentile

Percentiles (%) of Pr(*Network*)	Percent (%) Increase in Labor Productivity[a]	
Small Plants		
1% (0.5049) versus 99% (0.9805)	21.06%	
5% (0.6219) versus 99% (0.9805)	15.87%	
18% (0.7535) versus 99% (0.9805)	**10.06%**	
25% (0.7885) versus 99% (0.9805)	8.51%	
Medium Plants		
1% (0.8386) versus 99% (0.9886)	5.34%	
5% (0.8861) versus 99% (0.9886)	**3.65%**	
10% (0.9042) versus 99% (0.9886)	3.00%	
25% (0.9365) versus 99% (0.9886)	1.85%	
Large Plants		
1% (0.9228) versus 99% (0.9929)	- 4.67%	
3% (0.9379) versus 99% (0.9929)	**-3.67%**	
10% (0.9464) versus 99% (0.9929)	-3.10%	
25% (0.9577) versus 99% (0.9929)	-2.35%	
All Plants	Un-weighted[b]	Weighted[c]
1% (0.6085) versus 99% (0.9941)	11.95%	-23.75%
5% (0.7320) versus 99% (0.9941)	8.12%	-16.14%
10% (0.7941) versus 99% (0.9941)	**6.20%**	**-12.32%**
25% (0.8725) versus 99% (0.9941)	3.77%	-7.49%

[a] The estimated increases in labor productivity are calculated by comparing different points in the distribution of the predicted probabilities of having a computer network (Pr(*Network*)). For example, the first row compares plants in the 1st and 99th percentiles of the predicted probability of having a computer network. The increase in labor productivity of 19.98% is calculated as 0.443(0.9805-0.5049)=0.2106 (21.06%), where 0.420 is the estimated coefficient of Pr(*Network*) taken from Table 3.

[b] Percentage calculated using the estimated coefficient of Pr(Network) obtained from un-weighted two-stage regression.

[c] Percentage calculated using the estimated coefficient of Pr(Network) obtained from weighted two-stage regression.