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Abstract

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Abstract

How do computers affect productivity? Many recent studies argue that using information technology, particularly computers, is a significant source of U.S. productivity growth. The specific mechanism remains elusive. Detailed data on the use of computers and computer networks have been scarce. Plant-level data on the use of computer networks and electronic business processes in the manufacturing sector of the United States were collected for the first time in 1999. Using these new data, we find strong links between labor productivity and the presence of computer networks at the plant level. Plants with networks have higher average labor productivity. Computer networks show a positive and significant effect on labor productivity, controlling for capital intensity, skill mix, plant size, industry, and whether the plant is part of a multi-unit firm. Networks increase estimated labor productivity by roughly 10 to 20 percent, depending on model specification.

Keywords: Productivity, computer networks

1. Introduction

Many studies link the strong economic performance of the United States in the late 1990s economy to the use of computers. These studies took up the challenge of Solow's 1987 paradox that "you can see the computer age everywhere except in the productivity statistics." How computers affect performance remains an open question. Official statistics provided scant information about how computers are used. New data from the U.S. Census Bureau begin addressing this gap. The Computer Network Use Supplement (CNUS) to the 1999 Annual Survey of Manufactures (ASM) surveyed some 50,000 manufacturing plants about their use of on-line purchasing and ordering, the presence of computer networks, the kind of network (EDI, Internet, both), about 25 business processes (such as procurement, payroll, inventory, etc., conducted over computer networks; "e-business processes"), and whether those networked processes are used to interact internally, or with the manufacturing plant's customers or suppliers. The CNUS focused on the use of computer networks, rather than the presence of computers alone. The first official statistics, based on the responses of over 38,000 U.S. manufacturing plants, were released in June 2001.

This paper uses the new plant-level data on computer networks to estimate the effect of computer networks on labor productivity across manufacturing industries. Ours is the first study to make such estimates for the U.S. manufacturing sector. We link the CNUS supplement data to current and previous information for the same plant collected in the 1999 Annual Survey of Manufactures and the 1997 Census of Manufactures. Previous plant-level studies of the link between use of computer networks and productivity in the U.S. manufacturing sector were limited to five manufacturing industries covered in the 1988 and 1993 Surveys of Manufacturing Technology (SMT) collected by the U.S. Census Bureau.

Our research has two principal findings. First, average labor productivity is higher in manufacturing plants with networks than in plants without networks. Second, computer networks have a positive and significant effect on labor productivity after controlling for capital intensity, skill mix, plant size, industry, and whether the plant is part of a multi-unit business. Networks increase estimated labor productivity by roughly 10 to 20 percent, depending on model specification. This network effect is an important contributor to labor productivity, with an effect similar to the estimated 10 to 20 percent elasticities of capital intensity and skill mix.

We review the previous literature using plant-level data to estimate the effects of computer networks on productivity. Because the CNUS data we use are new, we describe them in some detail. We present our underlying economic model, derive empirical specifications, and describe the specific variables we use in the empirical analysis. We present the results of econometric estimates of our model, highlight our key findings, and discuss their implications. The research we present is the first estimates of the relationship between labor productivity and computer networks using these new data. Our results are preliminary, and we expect to refine and extend them. Some of those extensions will draw on the rich information the CNUS contains on the intensity and specific types of computer network use. We briefly indicate some directions we expect to take in future research using these new data.

2. Computers and Productivity: Previous Findings

The literature on the Solow paradox finds that the use of computers affects economic performance, including productivity. Computers, information technology (IT), and information and communications technology (ICT) often are used interchangeably in this literature. Many recent studies find that computers play an important role in the strong economic performance of the United States economy, particularly the surge of productivity growth in the late 1990s (e.g., Oliner and Sichel (2000); Jorgenson and Stiroh (2000); Jorgenson (2001); Stiroh (2001); Nordhaus (2001); and Triplett and Bosworth (2000)). Gullickson and Harper (1999) discuss a number of possible sources of measurement bias in aggregate productivity growth. Jorgenson (2001) finds that IT contributes substantially to the growth in total factor productivity throughout the 1948 – 1999 period, and particularly for the 1990s. That study finds both investments in IT and its use – consumption of IT services – contribute separately to the growth of gross domestic product, and recommends research distinguishing between using and producing computers.

International comparisons of the pervasiveness of ICT use among businesses and its effect on national economic performance also are underway. Some cross-country comparisons, (e.g. Schreyer (2000)), find a clear role for ICT in the U.S. and perhaps Japan, but not for other G7 countries. Official statistical surveys of the business use of ICT (including the use of a few e-business processes) have been initiated in many countries (e.g., Canada, Australia, Denmark, Finland, Norway, Japan, France, and the U.S. among others). International collaborations include the Nordic countries, which established a working group on ICT statistics, and the OECD's Working Party on Statistics for the Information Society, which is developing a model survey on ICT use by businesses (Boegh-Nielsen (2001)). Assessments of the effects of the ICT measured in these surveys are, of course, just beginning.

Computers may affect productivity in at least two ways. Computers may be used directly as inputs to the production process, as a specific form of capital. This is the approach taken in most existing studies, including both the national and industry-level studies cited above, as well studies at the plant or business level.

But computers may also be used to organize or streamline related business processes, such as order taking, inventory control, accounting services, and tracking product delivery. When these computers are linked into networks, they are electronic business processes (e-business processes; Atrostic, Gates, and Jarmin (2000)). Consider a steel mill. Computers and automated processes are used to control production processes in modern steel mills. Many support processes also can be computerized. For example, computers can be used to maintain a database of customers or shipments, or to do accounting or payroll. These computerized processes may be freestanding. Some of them may also occur over internal or external computer networks that allow information from a process to be exchanged readily. Shipments may be tracked on-line, inventories may be automatically monitored and suppliers notified when pre-determined levels are reached.

Adopting e-business processes automates existing business processes. It can also change the way companies conduct these processes and their businesses. The surge of interest in supply chains exemplifies this potential for computers to affect productivity growth outside of the manufacturing subsectors that produce them. These effects are thought to occur through organizational change. Many core supply chain processes are widely cited as examples of successful e-business processes that, in turn, are expected to shift the location of the process among the participants in the supply chain. Brynjolfsson and Hitt (2000) argue that the effects of organizational changes may rival the effects of changes in the production process. Viewed this way, computer networks are a productivity-enhancing technology.

Few studies assess the effect of computer networks on productivity. McGuckin *et al.*, (1996) use plant-level data for the five manufacturing industries included in the 1988 and 1993 SMTs. Grennan and Mairesse (1996) analyze panel data for French manufacturing and services firms over 1986 – 1990 and 1990 – 1994. Motohasi (2001) uses firm-level data for manufacturing, wholesale, and retail sectors in Japan in 1991. Motohashi (2001) and Brynjolfsson and Hitt find that IT affects total factor productivity only in firms with higher human capital and flatter workforce organization. However, causality is complex to model and the available micro data present challenges to economic measurement, so this literature does not yet shed definitive light on how IT affects productivity.

Official U.S. data on the use of e-business processes also has been very limited. The U.S. Census Bureau's Survey of Manufacturing Technology (SMT) was conducted in 1988 and 1993. Information was collected only from plants in the five major industry groups in manufacturing that were thought to be primary users of such technology: Fabricated metal products (SIC 34), Industrial machinery and equipment (SIC 35), Electronic and other electric equipment (SIC 36), Transportation equipment (SIC 37), and Instruments and related products (SIC 38). This data gap limited studies of e-business processes in the U.S. to the five manufacturing industries in the SMT (e.g., McGuckin *et al.*, (1996)), or to relatively small samples of firms drawn from proprietary data sets (e.g., 600 firms in Brynjolfsson and Hitt (2000)).

McGuckin *et al.* use the SMT data to examine the relationship between the use of advanced technologies and productivity and productivity growth rates in five manufacturing industries in 1988 and 1993. They find that diffusion differs across the several surveyed technologies. Productivity is higher at plants using advanced technologies, even after accounting for multiple economic characteristics of the plant. The relationship between productivity and advanced technology use holds both in terms of the number of technologies used and in the intensity of that use. But the use of advanced technologies does not necessarily cause higher productivity. In particular, McGuckin *et al.* conclude that the positive relationship between average productivity and the use of advanced technologies arises because operations that are performing well are more likely to use advanced technologies than poorly performing operations.

Atrostic and Gates (2001) use the new 1999 CNUS data to model two new indicators of the use of e-business processes in U.S. manufacturing: the use of computer networks, and of fully integrated enterprise resource planning software (FIERP). FIERP is a specific kind of enterprise resource planning software that integrates separate automated business processes such as payroll and procurements into a single system. They find computer networks are widespread within manufacturing. For example, they find that the Transportation equipment subsector (as classified in the North American Industrial Classification System (NAICS)) is one of the most intense users of fully integrated enterprise software, second only to the NAICS Electrical

Equipment subsector. While the estimates in Atrostic and Gates are based on plant-level responses, they are calculated from data aggregated to the subsector level, and their analysis does not address labor productivity.

3. New Data on Computers and E-Business Processes in U.S. Manufacturing

The Computer Network Use Supplement (CNUS) to the 1999 Annual Survey of Manufactures (ASM) surveyed some 50,000 manufacturing plants about their use of on-line purchasing and ordering, the presence of computer networks, the kind of network (EDI, Internet, both), about 25 business processes (such as procurement, payroll, inventory, etc., conducted over computer networks; "e-business processes"), and whether those networked processes are used to interact internally, or with the manufacturing plant's customers or suppliers. In June 2001, the U.S. Census Bureau released the first official statistics on the use of e-business processes (*E-stats*, at www.census.gov/estats). The statistics are based on responses of more than 38,000 U.S. manufacturing plants, with a response rate of 82 percent. All CNUS data are on a NAICS basis. Detailed information about the CNUS and ASM are contained in Appendix A.

The *E-stats* report highlights several e-businesses processes that appear closely related to the commercial activities of accepting and placing orders online. But manufacturing plants use networks for much more than on-line sales and orders. Only half of manufacturing plants reporting a network present also reported that they accepted and/or placed orders online. Research focusing on commercial transactions occurring online would omit uses of computer networks at roughly half of the plants reporting they use such networks. While the CNUS data clearly have the potential to provide new and exciting insights, the *E-stats* report is limited to presenting statistics about the use of e-business processes for respondents to the supplement.

4. New Estimates of the Effect of Computer Networks on Plant-Level Productivity

Assessing the effect of computer networks on productivity in manufacturing plants requires specifying a theoretical model of how computer networks affect labor productivity, then determining how best to implement it with the data available. In this section, we develop our theoretical model and describe how we implement it empirically. We use the newly available CNUS data to estimate plant-level labor productivity and the effect of computer network use on productivity. Data for responding plants is linked to information these plants reported in the 1999 ASM and the 1997 Census of Manufacturing to develop the variables required. We first examine whether average labor productivity differs in plants that use networks, then present and discuss the results of our econometric estimates.

A. Theoretical Model

To examine the effect of computer networks on labor productivity we specify the following Cobb-Douglas production function

$$Q = AK^{\alpha_1}L^{\alpha_2} \qquad (1)$$

where Q, K and L denote output, capital and labor, respectively. A is the usual "technological advance" term. The parameters α_1 and α_2 represent output elasticities of capital and labor.

To incorporate computer network (CNET) into the production function, we specify the technological advance term, A, as a function of CNET. That is,

$$A = e^{(\beta_0 + \beta_1 \text{CNET})} \qquad (2)$$

where CNET =1, if the plant has a computer network; else CNET=0.

Equation (2) is specified based on the idea that, at any given point in time, the plant that uses computer network in its production process is likely to produce a higher level of output than that of its counterpart that does not has a computer network. Technically, equation (2) is based on the assumption of "disembodied technical advance" that is not captured by K and L. That is, productivity can differ across plants even though they employ the same levels and types of inputs. In particular, in a cross-section study such as ours, differences in productivity across plants can be explained by plant-specific disembodies technical advance such as computer networks, which generate a positive externality to productivity. Thus we expect that β_1 is positive.

Substituting (2) into (1), dividing both side by L, and taking logarithms on both sides, we have

$$\text{Log}(Q/L) = \beta_0 + \beta_1\text{CNET} + \alpha_1 \log(K/L) + (\alpha_1 + \alpha_2 - 1)\log(L) \qquad (3)$$

Equation (3) directly relates computer network to log-labor productivity. In this formulation, β_1 is our parameter of interest. β_1 can be interpreted as measuring the effect of computer networks on labor productivity, controlling for capital intensity (K/L), and total labor, which, in turn, can be considered as a proxy for plant size. Note that if $\alpha_1 + \alpha_2 = 1$ (or $\alpha_1 + \alpha_2 -$ = 0), we have constant returns to scale. If $\alpha_1 + \alpha_2$ is less (greater) than 1, we have decreasing (increasing) returns to scale.

B. Empirical Specification

The theoretical model does not take into account other important plant characteristics that may significantly affect plant labor productivity. We therefore specify and estimate the following empirical model:

$$\text{Log}(Q/L) = \beta_0 + \beta_1\text{CNET} + \alpha_1 \log(K/L) + \alpha_3\text{SIZE}$$

$$+ \alpha_4\log(\text{SKILL}) + \alpha_5\text{MULTI} + \sum\gamma_i\text{IND}_i + \varepsilon \qquad (4)$$

Average labor productivity, Q / L, is the plant's total value of shipments (TVS) divided by its total employment (TE). Both the numerator and denominator of this ratio are reported on the 1999 ASM. Average value-added productivity is the plant's total value of shipments (Q) minus its cost of materials including energy (M), divided by its total employment. The costs of materials and energy both are reported on the 1999 ASM. While the value-added measure incorporates inputs other than labor, plant-level materials data in the ASM are known to be very noisy. Value-added measures are widely used in plant-level productivity analyses (e.g., McGuckin *et al.*, Greenan and Mairesse). Using both productivity measures allows us to consider whether our estimates seem sensitive to our choice of dependent variable, and to have estimates comparable to others in the literature. Unless specifically stated, results presented in this paper are based on labor productivity defined as the value of total shipments to employment.

Average labor productivity is higher in plants with computer networks. For manufacturing as a whole, labor productivity is nearly 30 percent higher in plants with computer networks. Both gross output and value-added labor productivity measures are shown in Table 1. The size of the productivity differential varies within manufacturing, but is of roughly similar magnitudes using either productivity measure. McGuckin *et al.*, found similar differentials in average labor productivity for a set of 17 advanced technologies involving the use of computers in the five SMT manufacturing industries.

"Network" is the key explanatory variable in this study. The new network variable, reported for the first time on the CNUS, takes on a value of one if the plant reported having a computer network, and zero otherwise. About 88 percent of the plants responding to the CNUS used computer networks (see Table 1). The CNUS network variable differs from what was available in earlier studies using the SMT. The SMT included three kinds of networks among its 17 advanced technologies, but did not ask whether any other kind of network was used. The CNUS asks whether the plant has a computer network, then queries about specific types of network and whether the plant uses each of two-dozen networked e-business processes.

Many plant-level productivity studies consider computers as an input, splitting capital into computer and non-computer measures. The perspective in our analysis is that using computer networks is a shift in technology, as specified in equation (2). This approach is also taken, for example, in McGuckin *et al.* (1998), Motohasi (2001), and Greenan and Mairesse (1996). Because we use the new CNUS data, our study of necessity is cross-sectional, rather than the longitudinal or panel study common in the plant-level productivity literature. In a cross-section, we assume existing production technologies are available to all plants, with competition yielding a rough convergence in productivity across plants of different ages and initial technologies (e.g., Jensen, McGuckin, and Stiroh (2000)). To continue the steel mill example, the new computer-controlled steel-making processes are available to all plants. Using computer networks to link computerized processes to track staffing, shipments requested by customers, or raw material deliveries needed or on order from suppliers, shifts the production frontier for given steel-making technologies. In practice, the CNUS data, like many other plant-level data (e.g., Mairesse and Greenan (1996)) show substantial variation among plants in both gross output and value-added productivity measures. At the three-digit NAICS level, gross output productivity for CNUS respondents ranges from 47 percent to over 400 percent of the manufacturing sector average.

"K/L" is the plant's capital / labor ratio as reported in the 1997 Economic Census. Capital is total asset value, that is, the book value of buildings and machinery. Labor in the denominator of this variable is total employment in 1997. We use 1997 data on capital intensity (K/L) because data on total capital stock are not available in 1999, which is not an Economic Census year. The measure is not adjusted for either capital or labor quality. We note that our capital measure is a stock measure, not a flow of services. However, developing plant-level service flows is beyond the scope of this initial research. We assume that the flow of services is proportional to book value. Following many other plant-level studies (e.g., McGuckin *et al.*, and Greenan, Mairesse, and Topiol-Bensaid (2001)), we use the book value of the capital / labor ratio as our measure of capital intensity.

Finer detail on capital stock and capital spending, particularly a split into computer vs. other machinery stock and spending would obviously be highly desirable in testing the separate effects of computers and the presence of computer networks on productivity. Such detail on computer investment, but not on the presence of networks, was collected in Economic Census years through 1992. Stolarick, 1999, for example, makes use of the computer investment measure in papers examining the relationship between productivity and computer and other information technology spending. However, he is not able to test for the effect of computer networks. Ideally, we would like to test for both computer investment and the presence of networks. However, computer investment *not* collected in the 1997 ASM. It will be collected in the 2000 ASM. Once those data are available, it will be possible to link responses for plants in the 1999 CNUS and the 2000 ASM. We are not able to make use of the considerable detail on computer spending collected in 1998 in another U.S. Census Bureau survey, the Annual Capital Expenditure Survey (ACES), because information is reported at the firm level, and cannot be linked readily with individual plants in the ASM.

"SKILL" is the ratio of the number of non-production workers to total employment in the plant, as reported on the 1999 ASM. Computer networks require highly skilled workers to develop and maintain them. Productivity might thus be higher at plants with a higher proportion of skilled labor because these workers are able to develop, use, and maintain advanced technologies, including computer networks. But applications such as expert systems may allow a function to be carried out with employees who have lower skill levels, or with fewer employees. Occupational detail would be desirable to test the relationship among productivity, networks, and the presence of such skilled occupations as computer programmers and systems support staff (e.g., Greenan, Mairesse, and Topiol-Bensaid (2001) and Motohashi (2001)). However, the ASM only collects information on the total numbers of production and non-production workers in the plant, with no further detail by process, function, or worker characteristic. Dunne and Schmitz (1992) found that plants in the 1988 SMT that used advanced technologies had lower ratios of production to total workers. We follow the precedent of many other plant-level studies (e.g., McGuckin *et al.*, and Dunne *et al.*) in using this employment ratio to proxy for skill mix in our productivity estimates. Production workers accounted for about one-quarter (27 percent) of employment among CNUS respondents in manufacturing. This share is similar to shares reported for the five two-digit U.S. Standard Industrial Classification (SIC) industries in the 1988 and 1993 SMTs (e.g., McGuckin *et al.* 1998).

The "SIZE" variable is based on total employment. We use three different proxies for SIZE. First we use log(L), where L is defined as total number of employees in the plant. This measure is used elsewhere, e.g., Greenan and Mairesse (1996). Note that because L enters both sides of the productivity equation it may introduce biases in the parameter estimates of the model. We therefore develop two additional measures of size. Our second measure classifies plants into six standard employment size groups: less than 50, 50 to 99, 100 to 249, 250 to 499, 500 to 999, and 1000 or more. We then assign a value of 1 for group 1, a value of 2 for group 2, etc. Our third measure specifies SIZE as a standard series of six dummy variables, that is, if total employment is less than 50 then size1 = 1; else size1 = 0, if 50 <total employment <100 then size2 = 0; else size2 = 0, etc. About 30 percent of the plants in our sample are in the smallest size class (fewer than 50 employees, 20 percent have between 50 and 99 employees, about 30 percent have between 100 and 250 employees, and the remaining 20 percent are in larger plants.

Many manufacturing plants are part of a multi-unit firm, so employment size alone is an inadequate indicator of available resources, managerial expertise, and scale. "Multi" is a dummy variable that takes on the value of one if the plant is part of a multi-unit firm, and equals zero otherwise. Nearly two-thirds of the plants in our sample are part of a mulit-unit firm.

All previous studies of plant-level behavior note substantial heterogeneity among plants within detailed manufacturing industries, as well as between detailed industries. There are 21 3-digit NAICS manufacturing industry groups in our sample (NAICS codes 311- 316, 321- 327 and 331-337). Industry dummies ("IND") are included in the empirical model specifications to capture industry-specific effects on plant-level labor productivity.

C. Empirical Findings

The preliminary results reported in this paper find that plants using computer networks significantly affects labor productivity. We already showed that these plants have higher average labor productivity, by any measure we calculate. Many of the expected relationships with explanatory variables hold, and are consistent across empirical model specifications. For a few explanatory variables, our results differ from theoretical expectations, but are consistent with some closely related empirical findings. We first report our preliminary estimates, then discuss their consistency with other research findings, and draw implications for future research.

i. Econometric Estimates

Computer networks significantly affect plant-level labor productivity. Labor productivity is 11 to 18 percent higher in plants that use computer networks, depending on how we empirically specify the model of labor productivity in equation (4). Tables 2 and 3 report the results of our estimates. The empirical specifications differ in how we measure plant size, and in whether we control for capital intensity.

In the first set of estimates, reported in Table 2, we define "size" as a continuous variable that takes on the value of 1 if the plant is small (fewer than 50 workers), 2 if employment is between 50 and 99, etc. The first two columns report results using our preferred measure of labor productivity, gross output per worker. Plants using computer networks have labor productivity that is 17 percent higher, controlling for skill mix, size, multi-unit firms, and industry subsector (column 1). The effect of networks remains significant and substantial, but decreases to 13 percent when we also control for capital intensity (column 2).

Capital intensity is positively and significantly related to labor productivity, with an elasticity of about 20 percent. Being part of a multi-unit firm matters. Productivity in plants that are part of multi-unit firms is nearly 50 percent higher than in single-unit plants, controlling for networks, skill mix, capital intensity, and size (column 1). When we control for capital intensity, we find that plants in multi-unit firms still have higher labor productivity although the differential falls to about 40 percent (column 2).

Skill mix is positively and significantly related to labor productivity in both specifications. The skill mix elasticity is about 22 percent when we do not account for capital intensity (column 1). In this specification, the estimated skill mix elasticity may be confounded by relationships between productivity and capital intensity. However, skill mix still has a significant elasticity of 18 percent when we control for capital intensity (column 2). This positive relationship is consistent with expectations that productivity is linked to the use of new production processes, including use of computer networks that require skilled workers.

Our estimates for these specifications are qualitatively similar when we use the alternate definition of labor productivity, value added per worker. Plants using computer networks have labor productivity that is 14 percent higher when we also control for skill mix, size, multi-unit firms, and industry subsector, but not for capital intensity (column 3). Controlling for capital intensity lowers the effect of computer networks to about 11 percent (column 4). Skill mix and capital intensity elasticities remain in the vicinity of 20 percent. Being part of a multi-unit firm still has a strong relationship to productivity, but the effects fall to about 35 and 30 percent (columns 3 and 4).

We find that larger plants have lower labor productivity. The coefficients on the continuous size measure in all model specifications in Table 2 are negative and most are significant. Unreported regressions using total employment as a size measure yield qualitatively similar results. Similar results hold for the separate size class dummies reported in Table 3. In each of the four model specifications, productivity relative to the smallest plant size (fewer than 50 workers) decreases as size class increases. We find returns to plant scale that are somewhat less than 1. We have looked quickly at several alternative specifications using these data, at coefficients reported in McGuckin *et al.*, and at coefficients using a different set of U.S. manufacturing panel data from a much earlier period, and find similar results.

Overall our estimates of the effect of computer networks on U.S. manufacturing productivity are similar to findings in McGuckin *et al.* for an earlier period and a limited set of manufacturing industries. In the specification most similar to ours, in their Table 7, computer networks and other communication and control technologies increase labor productivity by about 12 percent in 1993. Our estimate, in column 4 of Table 2, is about 11 percent. Their elasticity of capital intensity is about 14 percent; ours is about 18 percent.

ii. Discussion

The strong relationship we find between computer networks and productivity in U.S. manufacturing is consistent with the few other studies addressing this relationship in the U.S. or other countries (e.g., McGuckin *et al.* (1998) for five two-digit U.S. manufacturing industries; Greenan and Mairesses (1996) for France; and Motohashi (2001) for Japan). Most of the relationships we find between productivity and other explanatory variables also are broadly similar to those in previous studies. Finding strong effects of computers or computer networks in cross-section is consistent with a larger plant-level productivity literature. That literature also finds, however, that strong effects are harder to discern in panel and time-series studies (e.g. Mairesse & Griliches (1995)). Assessing how the cross-section findings hold up over time will require creative analysis because there is only one year of CNUS data.

Our most surprising finding is of slightly decreasing returns to scale for plant size. Being part of a larger corporate entity is strongly associated with increased labor productivity (the coefficient of "multi" discussed above). But given that corporate association, it is better to be a very small plant. While this finding is surprising, we note that it is consistent with other plant-level studies of U.S. manufacturing productivity, although previous studies do not comment on it. There are several possible interpretations. There may indeed be decreasing returns to plant size. But there may also be a correlation between the use of computer networks and capital intensity not captured in our empirical specification of the 1997 capital – labor ratio. Finally, we may be capturing a quality correction for capital, for which our current specification has no other proxy.

The relationship among size, skill mix, productivity, and computer networks is unclear a priori. Computer networks require investment and skilled staff to develop and maintain. Such investments may be more feasible for larger businesses. However, more recent network technologies such as the Internet are said to have become more feasible for smaller businesses because support services, such as Web hosting, can be purchased relatively inexpensively. Untangling these relationships will require further research, including industry-specific analyses and specifications, such as interaction terms, that explicitly seek to estimate multi-faceted relationships.

5. Conclusions

Labor productivity is significantly and substantially higher, on the order of 10 to 20 percent, in manufacturing plants that use computer networks. This finding is robust, holding up for two definitions of labor productivity and several alternative model specifications that control for capital intensity, skill mix, being part of a multi-unit firm, plant size, and industry. It also is consistent with other studies in the literature that look explicitly at the use of computer networks in the U.S. or in other countries. For the U.S., this is the first study to analyze the effect on productivity for the entire manufacturing sector.

This strong empirical regularity needs to be tempered with some standard caveats. Causality is difficult to infer in a cross-section study. Other studies suggest that unobserved differences in management practices or other aspects of organizing production activities are what cause the observed relationships. Better-managed plants may have higher productivity and also adopt computer networks. Our measures of the quality of labor, capital, and output all could be improved. Some of those improvements are relatively straightforward, and are part of our expected next steps.

The new CNUS data offer rich possibilities for further refinement and expansion of our analysis of how using computer networks and e-business processes affects productivity. We have not explored how the surveyed plants use computer networks. The CNUS data identify the business processes that are e-business processes, and whether those e-business processes are used to communicate within the firm, with customers, or with suppliers. Several studies find strong links to productivity when computers or computer networks (depending on study) are used in making the basic product, but less of a productivity payoff when they are used for processes like customer support or accounting and payroll has (e.g., Greenan and Mairesse (1996) for France; and Motohashi (2001) for Japan). One next step we will take is to use the new information on these processes for 1999 and see whether the patterns of strong and weak links to productivity found in these studies hold for the CNUS data. A second clear direction for future research is to extend our model specification to incorporate standard plant-level productivity specifications, such as within- and between-plant studies, adding information on the use of computer networks and e-business processes.

Table 1. Definitions and Means of Variables

Variable	Definition	Sample: Network	Sample: No network	Full Sample
Labor Productivity	TVS/TE	284.79	222.39	
Labor Productivity	VA/TE	133.65	103.29	
Average Employment	TE	235.70	118.64	
TVS	Total value of shipments.			
TE	Total employment (total number of production workers and non-production workers).			
VA	Total value of shipments minus materials and energy			
Labor Productivity	TVS/TE			277.34
Labor Productivity	VA/TE			130.03
TVS	Total value of shipments.			
TE	Total employment (total number of production workers and non-production workers).			221.72
VA				
Network	Network = 1 if plant uses a computer network			0.88
K	Total asset value (book value of building and machinery) in 1997			
KL97	Capital/labor ratio in 1997 (K97/TE97).			107.50
Skill mix	OW/TE			0.27
OW	Non-production workers			
Multi	Multi =1 if the plant owned by a multi-plant firm			0.64
	If TE < 50 then Size =1;			0.29
	if 50 < = TE < 99 then Size = 2;			0.19
	if 100 < = TE < 250 then Size = 3;			0.28
	if 250 < = TE < 499 then Size = 4;			0.14
	if 500 < = TE < 999 then Size = 5;			0.07
Size	if TE > = 1000 then Size = 6.			0.03
Industry	Three-digit NAICS subsectors 311 to 316; 321 to 327; & 331 to 337			N/a

Table 2. Productivity Regression Results

***Dependent Variable**: Labor Productivity (TVS/TE or VA/TE)*
(T-statistics in parentheses)

Independent Variables	Dependent variable: Labor Productivity defined as			
	Gross Output (TVS/TE)		Value-Added (VA/TE)	
	(1)	(2)	(3)	(4)
Intercept	3.991 (176.38)	3.553 (157.11)	3.466 (145.69)	3.103 (127.67)
Network	.172 (14.82)	.134 (12.17)	.138 (11.34)	.109 (9.18)
Skill	.221 (47.38)	.183 (41.00)	.216 (43.88)	.184 (38.24)
KL97	(–) (–)	.202 (64.38)	(--) (--)	.167 (49.32)
Size	-.024 (8.15)	-.037 (12.87)	-.002 (0.70)	-.012 (3.92)
Multi	.486 (56.76)	.386 (46.83)	.355 (43.88)	.272 (30.59)
Industry (3-digit NAICS)	Yes	Yes	Yes	Yes
R^2	.34	.41	.22	.27
Number of plants	35,506	35,146	35,175	34,819

Table 3. Productivity Regression Results

Dependent Variable*: Labor Productivity (TVS/TE or VA/TE)*
(T-statistics in parentheses)

Independent Variables	Dependent variable: Labor Productivity defined as			
	Gross Output (TVS/TE)		Value-Added (VA/TE)	
Intercept	3.973 (178.20)	3.523 (157.38)	3.473 (148.05)	3.101 (128.75)
Network	.180 (15.46)	.142 (12.75)	.148 (12.02)	.117 (9.79)
Skill	.219 (46.99)	.181 (40.68)	.214 (43.60)	.183 (38.03)
KL97	(--) (--)	.202 (64.18)	(--) (--)	.167 (49.15)
Multi	.492 (57.27)	.392 (47.30)	.361 (39.87)	.277 (31.06)
Size2	-.031 (2.94)	-.042 (4.21)	-.023 (2.07)	-.031 (2.84)
Size3	-.073 (7.16)	-.094 (9.72)	-.037 (3.49)	-.053 (5.15)
Size4	-.129 (8.52)	-.155 (12.91)	-.057 (4.25)	-075 (5.86)
Size5	-.137 (8.52)	-.183 (12.06)	-029 (1.74)	-.066 (4.09)
Size6	.040 (1.83)	-.044 (2.11)	.103 (4.41)	.033 (1.49)
Industry (3-digit NAICS)	Yes	Yes	Yes	Yes
R^2	.34	.41	.22	.27
Numbers of Plants	35,507	35,146	35,176	34,819

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