# COMPUTER INVESTMENT, COMPUTER NETWORKS, AND PRODUCTIVITY

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Abstract

Researchers in a large empirical literature find significant relationships between computers and labor productivity, but the estimated size of that relationship varies considerably. In this paper, we estimate the relationships among computers, computer networks, and plant-level productivity in U.S. manufacturing. Using new data on computer investment, we develop a sample with the best proxies for computer and total capital that the data allow us to construct. We find that computer networks and computer inputs have separate, positive, and significant relationships with U.S. manufacturing plant-level productivity.

Keywords: computer input; information technology; labor productivity

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## I. Introduction

Computer networks may be a new technology that shifts the production function. Our previous research (Atrostic and Nguyen, 2004) found a positive and significant relationship between computer networks and plant-level productivity in U.S. manufacturing productivity, using the first survey data on the presence of computer networks in manufacturing plants, collected in the 1999 Computer Network Use Survey (CNUS). We controlled for other inputs to production, plant characteristics, and the endogeneity of computer networks. However, because no data to proxy for the capital stocks of computers were available, our previous estimate of the relationship between computer networks and plants' labor productivity may be subject to an omitted variable bias.

This paper extends our previous model to include computer capital as a separate input in the production function. We use new plant-level data on computer investment from the 2000 Annual Survey of Manufactures (ASM) to develop the proxy for computer capital inputs. An important contribution of this paper is to define the sample for which the measures of computer and conventional physical capital available in the data are good proxies for these capital inputs. We show that these measures are good proxies only for plants that are new. For new plants, capital theory implies that computer investment equals the value of the plant's computer stock, and book values of buildings and machinery equal the plant's value of physical capital stock. We create a sample of new plants with the conceptually best proxies possible with the available data. Using this sample, we find positive and significant relationships between U.S. manufacturing plant-level labor productivity and both computer networks and computer capital inputs. Our findings suggest that we need separate measures of computers and new technologies using them to understand the relationship between computers and productivity.

## II. Computers, Computer Networks, and Productivity: Measurement Issues

Estimating plant-level relationships among computers, computer networks, and productivity requires overcoming many empirical challenges. Researchers must address the substantial standard measurement issues that arise in using plant-level data (see Griliches 1994 and Griliches and Mairesse 1995). Serious data gaps specific to the quest to understand the economic role of computers, electronic devices, and computer networks limit the available measures of computers and related information technologies, and computer networks (see, for example, Atrostic, Gates, and Jarmin 2000; Haltiwanger and Jarmin 2001; Stiroh 2002). The resulting empirical literature on computers and productivity is plagued with measurement issues that likely contribute to its divergent findings (Stiroh 2002). In this section, we focus on three specific issues, measuring capital inputs in general, measuring computer capital inputs, and estimating the relationship between computer networks and productivity.

### A. Measuring Capital Input

Our productivity model requires a measure of capital inputs or capital services. Such a measure, or the data needed to create it, is hard to get directly. Researchers have developed ways to use the information that is typically available to create proxies for capital inputs that are widely used in both time-series and cross-section analyses. However, our data lack the information needed to create these standard proxies.

For time-series analysis, a measure of capital services can be generated from information on the capital stock. The perpetual inventory method usually builds the capital measure up from data on capital investments, depreciation and asset prices. That is $K_t = K_0 + \Sigma\Delta K^{\tau}$ ($\tau = 0, \ldots, \tau - 1$), where $\Delta K^{\tau} = (I_t - D_t)/P_t$ and I , P and P denote capital investments, depreciation and asset prices. A problem with the perpetual inventory method, especially at the plant level, is that data on depreciation and asset prices are not available.

An alternative method uses the book value of capital as a proxy for the capital stock. An advantage of this approach is that book values are frequently collected directly from respondents. A major shortcoming of book values is that they are evaluated at the purchase prices, regardless of the timing of that purchase. Therefore, except for special cases, book values do not reflect the true value of capital stocks.[1]

The plant-level study by Baily *et al*., (1992) finds that both perpetual inventory and book value measures lead to similar empirical results for topics such as productivity dispersion. Doms

[1] To alleviate this problem, researchers often use plant ages and other plant characteristics as controls in their regressions models when using book values as a proxy for capital inputs .

(1996) also finds that book values and service flows measures yield similar results for a specific set of advanced technologies. Because of these empirical regularities, many researchers who use plant-level data (e.g., Doms *et al*., 1997; McGuckin *et al*., 1998; Dunne *et al.* 2000; and Greenan *et al*., Mairesse, and Topiol-Bensaid 2001) use the book values of the plant's total capital stock directly as a proxy for service flows. Stiroh's recent analysis (2002) also finds little empirical difference between the two measures.

For cross-section analysis, it is often impossible to construct a measure of capital services using the perpetual inventory method because the necessary time-series of capital investment data are not available. Empirical cross-section studies often use book values of the capital stock as a proxy for capital services, assuming capital input is proportional to book values. This assumption may be correct if all plants in the sample have the same age. But this is not likely to be the case. Because book values are evaluated at the purchase price and plants in the sample differ in ages, book values of capital seriously mis-measure the plant's capital inputs.

Data gaps for recent years threaten the empirical similarities found in earlier years between book value and service flows measures. Book values of physical capital (buildings and machinery) are now collected less frequently in U.S. manufacturing, and for a smaller group of plants, than in the past. Book values were collected annually in both the CM and ASM until 1986. Since then, these data are collected only for the roughly 55 thousand plants that are in the ASM sample in the Economic Census years (e.g., 1987, 1992, and 1997), and not for the roughly 350 thousand plants that are in the 1997 CM (U.S. Census Bureau 2001).

### B. Measuring Computer Input

Computers should be treated as a separate capital input in production and productivity analysis, as suggested by studies such as Jorgenson and Stiroh (2000) and Oliner and Sichel (2001). Computer services are the theoretically appropriate measure of computer input. Computer services, like other capital services, are not observed, and measures approximating this service flow must be constructed. Computer service flows are normally estimated from measures of the computer capital stock in aggregate and industry-level productivity studies (e.g., Jorgenson *et al*., 2002; Triplett and Bosworth 2002). However, book values of computer capital are not collected in government data, so studies using plant-level data often approximate computer service flows with measures of computer investment.

Investment has been used as a measure of the presence of computers, or of computer intensity, or as a measure of the intensity of technology use in many recent plant-level studies. Computer investment per worker is used as a proxy for computer input per worker in the plant in Berman *et al*. (1994). Doms *et al*. (1997) control for computer investment in their analysis of how adopting various technologies affects a series of plant-level economic outcomes. Dunne *et al.* (2000) examine the role of computer investment in the dispersion of productivity and wages in U.S. manufacturing. Haltiwanger *et al*. (2003) use computer investment as a factor separate from total equipment investment in estimating productivity.

Computer investment is a good proxy for computer capital stock under the assumption that this investment is equal or proportional to a plant's stock of computer capital. This assumption allows researchers to use the only measure at hand. However, it may not be correct. Total plant-level investment typically is lumpy, while service flows are not. Cooper *et al*. (1999) find that plant-level investment surges are followed by periods of low investment. Becker *et al.* (2004) look at more recent data and find investment spikes in both firm- and plant-level data for investment in general. Recent research by Wilson (2004) suggests that firm-level investment may be lumpy across specific kinds of investment, including computers and communications equipment. However, this result is based on the single available cross-section of detailed investment data, so the lumpiness of investment can only be defined in terms of the share of a firm's investment in specific kinds of capital goods, rather than variation over time in the amount and kind of investment.

Actual investment to make computers usable in the workplace (co-invention) may be less lumpy than measured computer equipment investment. Co-invention includes expenditures developing and implementing software that engages and connects computers and adapts them to plant-specific uses, e.g., Bresnahan and Greenstein 1997; as well as changes in workplace organization, management, and other organizational capital that make more effective use of computers, labor, and other inputs, e.g., Brynjolfsson and Hitt 2003. Some of these expenditures may be capitalized, but others may be expensed. Co-invention may continue in periods when there is no investment in computer hardware and software. Because the scale of co-invention over the life of the computer asset can be as much as the original computer equipment investment (Bresnahan and Greenstein 1997), or up to 10 times the investment in computer hardware (Brynjolfsson and Hitt 2003), the joint effect may be to smooth or exacerbate investment lumpiness. These unmeasured complementary computer investments may cause estimated returns to measured computer investments to exceed actual returns to measured computer investments, particularly in the long run (e.g. Brynjolfsson and Hitt 2003). However, any effect of co-invention on actual computer investment will not be captured in our measure because only data for investments in computer hardware and peripherals are collected in the 2000 ASM.

Data gaps for recent years also limit the available computer investment data. These data are collected only occasionally, and in recent years were not collected at the same time as book values of capital. While computer investment data were collected in the CM for 1977 through 1992, they were not collected at all in 1997 (when book values of physical capital were collected), and were only collected again in the ASM in 2000 and 2001 (when book values of physical capital were not collected). The lumpiness of plant- and firm-level investment means that investment data for a single year are not a good proxy for the plant's (or firm's) stock, except for new plants. In a new plant, capital investment would be equal to the value of the plant's capital stock.

**C. Developing a Sample with Good Proxies for Computer and Capital Inputs**

The data gaps for recent years make it difficult to argue that the data we have available on book values of capital and computer investment provide equally plausible proxies for total capital and computer services for *all* plants that responded to the CNUS. In this paper, we develop the conceptually best sample of CNUS respondents that our measures of computer and total capital allow us to make: a sample of plants that first appeared in the 1997 CM. When a plant is new, the book values of physical capital (buildings and machinery) and computer investment should equal the value of the plant's capital stock and the plant's computer capital stock, respectively. While this is the best sample the data allow, its proxies are not as good as in the past. Neither the book values of computer stock nor computer investment were available in 1997. The best proxy we have for computer capital is the computer investment data collected in the 2000 ASM.

If we were estimating productivity in 1997, it would be straightforward to use the book values of total capital that these new plants report in the 1997 CM as a proxy for their total capital services in 1997, making the standard assumption that capital services are proportional to the value of the capital stock. That is, for physical capital, $K_{T1997} \equiv BV_{T1997,}$ where K is the value of the plant's total physical capital stock, T indexes total capital, and BV is book value.[2] However, we estimate productivity in 2000 (rather than 1997) because computer capital input is measured in 2000, and most of the remaining variables, particularly the variable of interest, computer networks, are measured in 1999[3]. We therefore use standard capital theory to relate the flow of total capital services in 2000, $S_T(K_{T2000})$ to total book value in 1997 for our sample of plants new in 1997:

(1) $S_T(K_{T2000}) \approx \pi_T \cdot BV_{T1997} \cdot \delta_{T\tau.}$

The proportionality factor, $\pi_T$, represents services per unit of total capital. The approximation error, $\delta_{T\tau.}$, increases as 1997 differs from the year for which we wish to measure capital services. That is, $\delta_{T\tau} > \delta_{T\upsilon}$ when $|\tau - 1997| > |\upsilon - 1997|$ for plants observed in year $\tau$ compared to year $\upsilon$.

For computer capital stock in 2000, we use computer investment in 2000 as a proxy under the assumption that the total computer capital stock is proportional to observed investment:

(2) $K_{C2000} \approx \gamma \cdot I_{C2000}$,

where $K_{C2000}$ represents the plant's actual computer capital stock and $I_{C2000}$ is the plant's computer investment in 2000. The proportionality factor, $\gamma$, is positive ($\gamma \geq 1$) and assumed to be the same for all plants in our sample because they opened in the same year, 1997. If $\gamma = 1$, the plant completely replaces its old computing stock with new computers. When $\gamma > 1$, the plant only replaces a portion of its computer capital stock each year.

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[2] We first link all observations that have both information on computer networks in the 1999 CNUS and information on computer investment in the 2000 ASM. Because the 1999 CNUS and 2000 ASM samples each are drawn from a sample frame based on the 1997 CM, the probability-proportionate-to-size sampling strategy leads to a high overlap between the two samples, and the 1999 – 2000 linking rate is high. Haltiwanger, Jarmin, and Schank (2003) find little sample reduction when they link the 1999 CNUS and the 2000 ASM. Their final sizes range from 22,700 to 22,900, depending on specification.

Because the data as entered in the CES data storage system do not allow us to distinguish between plants that do not report computer investment and those that report zero, we exclude both. This means that the plants in our sample all have positive computer investment. We find that roughly one-third of the linked plants report positive computer investment. This response pattern is consistent the historical pattern when this item was collected in 1977, 1982, 1987, and 1992 (e.g., Dunne *et al*. 2000). From the linked sample we select plants that first appeared in the 1997 CM (that is, they did not appear in the 1992 CM or the 1993 through 1996 ASMs).

[3] Because computer networks are major investments, and U.S. manufacturing plants have used some form of networks for decades, it seems reasonable to assume that plants with networks in 1999 will continue to have networks in 2000.

We again use standard capital theory to relate the flow of computer capital services in 2000, $S_C(K_{C2000})$, to our proxy for the computer capital stock:

(3) $S_C(K_{C2000}) \approx \pi_C \cdot K_{C2000.} \cdot \delta_{C\tau}$,

where the proportionality factor, $\pi_C$, represents services per unit of computer capital, and $\delta_{C\tau}$ is the approximation error from using investment data in 2000 to measure computer service flows in 1999.

Using these proxies yields the conceptually best sample that the data will allow us to create. The sample of plants new in 1997 has 849 observations. We address the concern that the sample is small by constructing a second sample based on a broader alternative definition of new that includes plants between three and eight years old. The broader definition includes plants that first appeared in the 1993 through 1996 ASMs and have positive computer investment. These plants are between three and eight years old in 2000, below the 10-year average age of plants in the 1999 CNUS – 2000 ASM linked data set.[4] The value of the capital approximation errors, $\delta_{T\tau}$ and $\delta_{C\tau}$, will be higher for these plants than for plants that are new in 1997, but including them yields a larger sample of 1,755 observations.

To test the importance of using the sample of plants for which we have relatively better proxies for total and computer capital stock, we use the linked data to construct a data set containing plants of all ages. Our sample of plants of all ages that report positive computer investment has 12,386 observations.

### D. Estimating the Impact of Computer Networks

We want to estimate the impact of computer networks because they may be a new technology that shifts the production function. Simply using computers seems unlikely to be such a shift, since computers have been in commercial use in the U.S. for fifty years, and they might be viewed as just another capital input. Computer networks also have been used for decades. But the networks that came into use more recently are thought to be qualitatively different (e.g., Bresnahan and Greenstein 1997). Brynjolfsson and Hitt (2000) argue that the effects of organizational changes caused by the newer computer networks may rival the effects

[4] Haltiwanger, Jarmin, and Schank (2003).

of changes in the production process. Viewed this way, computer networks are a productivity-enhancing general-purpose technology (Breshnahan and Trajtenberg 1995). The question for productivity and other measures of economic performance may no longer be whether computers matter, but whether it matters how computers are used.

Despite the importance of understanding whether computer networks matter for productivity, information on networks is scarce. The computer network information collected in the 1999 CNUS is the first such collection for a large and representative national sample of plants in U.S. manufacturing. The CNUS asked about the presence of several kinds of networks, including Internet, Intranet, Local Area Networks (LAN), Electronic Data Interchange (EDI), Extranet, and "other." We create a dummy variable for the presence of computer networks that takes on a value of one if the plant reports having any of these kinds of computer network, and zero otherwise.

The 1999 CNUS network data, together with the computer investment information collected in the 2000 ASM, allow us for the first time to specify an empirical model of labor productivity with separate measures of the presence of computers (computer investment) and how computers are used (computer networks). Having separate measures is important because a standard empirical finding in plant-level cross-section estimates is that the omitted variables problem may be serious. Using only the information on how businesses use computers (the presence of computer networks), as in our previous research, may overstate the importance of those uses because it is picking up the importance of having computers.

There are straightforward implications for economic measurement if we find that networks have a separate effect on productivity. Having a computer network is a simple and clear indicator of how plants use computers. Computer networks might also proxy for previous computer investment. Relatively little information needs to be collected to construct a network measure. If this measure alone conveys important information about firm heterogeneity in the uses of computers, and in particular on the newest uses, it is worth considering eking out room for its components in survey instruments and respondent burden calculations.

## III. Empirical Implementation

To assess the relationship between computer networks and computer input on plants' labor productivity, we estimate the following equation, based on a Cobb-Douglas production function:

$$(4) \quad \text{Log}(Q/L) = \beta_0 + \beta_1 CNET + \alpha_{1c}\log(K_c/L) + \alpha_{1nc}\log(K_{nc}/L) + \alpha_2\log(M/L) + \alpha_3\log(MIX) + \alpha_4 MULTI + \sum\gamma_j SIZE_j + \sum\lambda_i IND_i + \varepsilon$$

where Q, $K_c$, $K_{nc,}$ L, and M represent output, computer capital input, non-computer capital input, labor, and materials. CNET denotes computer networks. SIZE denotes the size class of the plant. MIX denotes the mix of production and non-production workers, and MULTI represents plants that belong to a multi-unit firm. IND denotes three-digit NAICS industries.

Our model distinguishes between the productive effect of computer input in the plant and a technological shift resulting from using computer networks. Equation (4) directly relates computer networks and computer capital to (log) labor productivity. In this formulation, $\beta_1$ is one of our two parameters of interest. It can be interpreted as measuring the effect of computer networks on labor productivity, controlling for the intensities of computer and non-computer capital ($K_c/L$ and $K_{nc}/L$), and materials intensity (M/L).

The second parameter of interest is $\alpha_{1c}$, the coefficient on the intensity of computer capital. This coefficient can be interpreted a return to the flow of services from the stock of computer capital, controlling for the presence of computer networks and other inputs.

In this paper, we focus on estimating whether labor productivity is related both to computer networks and computer inputs. Labor productivity is defined as output per worker, (Q/L). We use total value of shipments (TVS) as a measure of Q. Our measure of labor, L, is the total number of employees in the plant. Our model differs from those in most previous related plant-level studies in specifying a three-factor production function in which output is defined as gross output (rather than value added) and materials are incorporated as a separate input in production.

We described earlier how we use the CNUS, ASM, and CM to specify computer networks, computer inputs, and total capital inputs. We use the same empirical specifications of materials, skill mix, size, multi-unit plant status, and industry as Atrostic and Nguyen (2004). The CNUS data are part of a Census Bureau measurement initiative to fill some of the data gaps on the growing use of electronic devices and networks in the economy (Mesenbourg 2001). The appendix contains more information on the 1999 CNUS, 2000 ASM, and the 1992 and 1997 CM.

## IV. Empirical Findings

We estimate relationships among computers, computer investment, and labor productivity using three alternative specifications. The preferred specification includes both computer networks and computer inputs. A specification that parallels our prior research includes computer networks but not computer inputs. The third specification parallels specifications in the literature that include computer inputs but not computer networks.

The three specifications are estimated first for the cohort of 849 plants that newly opened their operations in 1997 and had positive computer investment in 2000. We report these results in Table 1. To assess whether it matters that we restrict our sample to plants that were new in 1997, we estimate the same three specifications using two other samples. Estimates from the sample of 1,755 relatively new plants that opened between 1993 and 1997 and have positive computer investment in 2000 are reported in Table 2.[5] Estimates from the sample of 12,836 plants of all ages that have positive computer investment in 2000 are also reported in Table 2. This data set allows us to assess the empirical importance of using proxies for capital services when they are unlikely to be good measures. Because information on computer networks was collected only in 1999, our analyses are all cross-sectional.

Computer investment and computer networks both have positive and significant relationships to labor productivity in estimates from our preferred specification, as reported in column (1) of Table 1. The coefficient on computer networks is 0.117, controlling for computer and other inputs and plant characteristics.[6] Computer investment has a separate and significant effect, with a coefficient of computer intensity ($K_c/L$) of 0.050. Computer networks are

[5] We also create four sub-samples of plants that are new in each year between 1997 and 1992. The results are similar to the results for plants new in 1997, and all plants that are new between 1992 and 1997, so we do not report them separately.

[6] The exponential of the coefficient 0.117 is 1.124, or a differential of 12.4 percent. However, because the differences between the exponential and the coefficient are not large, we discuss the coefficient rather than the exponential in the text.

significant when they enter the estimation alone, and the coefficient of 0.136, reported in column (2), is higher than when computer investment is included. When computer networks are excluded and computer investment is included alone, computer intensity is significant, with the slightly higher coefficient of 0.052 as shown in column (3) of Table 1.[7] These estimates show that it matters empirically whether data are available to proxy for both computer networks and computer inputs. Each coefficient is higher in the specification that excludes the other measure, suggesting that when each is used alone, it picks up part of the impact of the other.

The coefficient of one other variable, MIX, the ratio of non-production to production workers, changes appreciably across these specifications. In our preferred specification that includes both computer investment and networks (column (1) of Table 1), the coefficient of MIX is 0.040, but is not significant. An estimate similar in size, 0.044, and in lack of significance, comes from the specification that includes only computer investment (column (3)). By comparison, in the specification that only includes computer networks, the coefficient of MIX increases to 0.061, suggesting that computer inputs may be positively related to the worker mix ratio (column (3)). Other researchers find similar relationships between worker mix and computer investment (e.g., Dunne *et al.* 2000, and Haltiwanger, Jarmin and Schank 2003). Coefficients of most other inputs, plant characteristics, and $R^2$, change little across the three specifications reported in Table 1, suggesting that the computer network and computer input measures are independent of other inputs or plant characteristics.

We assess the sensitivity of these estimates to the assumption that our proxies for capital and computer service flows are best for new plants by estimating the same three specifications using our five samples of new plants. Because the empirical findings are qualitatively the same for all five samples, we report in Table 2 the findings for the largest sample of 1,755 plants that are new between 1992 and 1997.

This broader definition of "new" plant yields similar findings. Computer investment and computer networks both have positive and significant relationships to labor productivity, as reported in column (1) of Table 2. The computer network coefficient of 0.126 is significant for relatively new plants with computers, controlling for computer and other inputs and plant

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[7] While we calculate coefficients for industry dummies $\lambda$, and for size dummies $\gamma$, we do not report them because such coefficients present standard micro data disclosure problems.

characteristics. Computer investment has a separate and significant effect, with a coefficient of computer intensity ($K_c/L$) of 0.046. When computer networks are excluded, computer intensity remains significant, with a slightly higher coefficient of 0.049, as shown in column (2) of Table 1. When computer inputs are excluded and computer networks are included alone, computer networks remain significant, with a higher coefficient of 0.1510.

Having good proxies for all forms of capital services is empirically important. Coefficients of both computer networks and computer input are significant in all the estimates based on new plants, as reported in Tables 1 and 2. A very different picture emerges from estimates based on plants of all ages. In these estimates, computer networks and computer inputs do not each have empirically separate relationships with labor productivity. The network coefficient of 0.004, reported in column (4) of Table 2, is not statistically significant. Computer investment, however, is positively and significantly related to productivity, with a coefficient of 0.0478.[8] Using this sample, computer networks do not appear to be a technology that shifts the production function, distinct from the productive effect of computer inputs. Instead, computer networks appear simply to be a measure of computer inputs. However, our proxies for total and computer capital inputs are most problematic for this sample.

## V. Discussion

Our empirical findings suggest that using computer networks may be a new technology that shifts the production function and is separate from simply using computers. The measurement issues we raise about capital inputs have important empirical consequences, because those findings hold only when we have good proxies for capital inputs. When we lack good proxies, we would conclude instead that our cross-section estimates of the separate relationships of productivity with computer networks and computer inputs are subject to omitted variable bias, and that the new network variable yields no additional information about the

[8] We report only OLS estimates. Because we use new, or relatively new, plants, we have no good instruments. The two-stage estimates reported in our prior research did not have the expected result of reducing the estimated effect of computer networks. When we estimate OLS specifications on the same sample used in the two-stage estimates, coefficients of variables other than networks and computer investment are stable.

relationship between computer use and productivity in U.S. manufacturing.

We assess these findings by comparing them with results we obtained in our previous study using these data, when only information on computer networks was available, and with results of other researchers. The final portion of this section discusses two aspects of data gaps: How remaining data gaps may affect our estimates, and what our findings imply for priorities in filling them.

### A. Comparison with Prior Research Using These Data

Our findings in this paper are consistent with our previous research using these data, which showed significant and positive impacts of computer networks on labor productivity in both OLS and two-stage regressions (Atrostic and Nguyen 2004). The appropriate comparison is with computer network coefficients from OLS regressions on the 10,496 observations that we also used in the two-stage estimates. Those OLS estimates, repeated here in column (2) of Table 3, show that labor productivity is 3.9 percent higher in plants with networks.[9]

The new estimates we report for the productivity impact of networks for plants are much higher than we found in our previous research. However, our previous and new estimates are not directly comparable because the samples differ in two ways. The sample we use in this paper is for plants that are new in 1997 and have computer investment. Our previous research includes plants of all ages, and, because data on computer investment in 2000 were not available, did not use its presence to define the sample.[10]

With those two differences in mind, we compare the specification that is most similar in the new and previous research, which includes computer networks but not computer inputs. Coefficients for computer networks and the worker mix variable differ between the

[9] In contrast to standard findings in estimates from OLS vs. two-stage regressions, our previous research shows a positive and significant computer network effect in both, and the effect estimated in the two-stage regressions, 7.2 percent, exceeds the OLS estimate of 3.8 percent. We obtain the 7.2 percent estimate by evaluating the significant coefficient of the predicted network variable (0.669) at the mean of the network variable.

[10] We also perform parallel sensitivity assessments between the 12,836-observation data set of plants of all ages that we use in this paper 10,496-observation 1999 CNUS-only data used in our previous research (Atrostic and Nguyen 2004a). Because the same specification estimated on these two data sets yield similar results to those reported here, we do not discuss them separately.

specifications, but the remaining coefficients are broadly similar across the samples reported in Tables 1, 2, and 3.

The estimated computer network impact is 14.6 percent for plants new in 1997 (the exponential of the coefficient 0.136 in column (2) in Table 1). This is nearly four times the 3.9 percent impact of networks for plants of all ages in our previous research. Our finding that the coefficient of computer networks is higher for newer plants might seem to lend some support to the vintage capital model, on which the existing empirical literature yields mixed findings (Bartlesman and Doms 2000).[11] However, what our research finds is that computer networks have a higher productivity *impact* in newer plants. Those new plants have lower average productivity, regardless of whether they have networks. Also, the new findings we report in this paper are for plants that had positive computer investment in 2000. Investing in computers may signal a relative ability to exploit network technology.

The coefficient of the MIX term, the ratio of non-production to production workers also is higher for the new plants (0.061 vs. 0.039). This suggests that newer plants that are more productive have a higher proportion of non-production workers. Higher ratios of non-production to production workers are frequently taken as proxies for higher levels of skills embodied in the workers. Careful research linking the broad groupings of production and non-production workers with reports from the 1990 Decennial Census of actual worker education suggests that there can be such embodiment (Doms, Dunne, Trostke 1997). However, we cannot make such linkages with our data. The broad worker classification in the MIX term makes it difficult to read too much into any estimated difference in this coefficient between groups of plants of different ages.

### B. Comparisons with The Information Technology Literature

[11] The vintage capital model says that newer plants open with the newest, embodied technology, and that plants exit when their productivity becomes too low relative to the new entrants. Consistent with the model are results in the literature suggesting that older plants are more likely to exit, but more productive plants are more likely to continue. However, Baily, Hulten, and Campbell (1992) find little evidence for the vintage capital model in examining transition matrices across years in U.S. manufacturing. They and other researchers find that plants entering an industry have low productivity on average, but move within a few years to both the highest and lowest productivity groups. Similarly, Power (1998) finds that productivity increases with plant age, but finds almost no relationship between productivity and the age of investments.

Our finding of positive and significant relationships between computers and computer networks and productivity is consistent with the recent empirical literature and the plant and firm level. Previous research using the computer investment data for U.S. manufacturing through 1992 found a positive link with plant-level productivity, with much variation among industries (Stolarick 1999 a and b). Two recent reviews of plant- or firm-level empirical studies of information technology (including but not limited to computers) and economic performance (Dedrick *et al.* 2003 and Stiroh 2002) conclude that the literature shows positive relationships between information technology and productivity.

Dedrick *et al.* (2003) review over 50 articles published between 1985 and 2002, many of which are firm-level studies with productivity as the performance measure. They conclude that firm-level studies show positive relationships, and that gross returns to information technology investments exceed returns to other investments.[12]

Stiroh (2002) conducts a meta-analysis of twenty recent empirical studies of the relationship between information technology and the production function. He also estimates a number of specifications used in those studies on a single industry-level database. The meta-analysis of 19 firm-level studies that use gross output productivity measures yields a mean elasticity of information technology of 0.042, with large variability around that coefficient. His estimates using the single industry-level database yield OLS estimates of computer capital elasticity of 0.047.[13] The coefficient estimate, however, is sensitive to econometric specifications that account, for example, for unobserved heterogeneity.

Stiroh's meta-analysis and basic OLS regression estimates are close to the coefficient of 0.050 that we report for computer capital elasticity in new plants, in our preferred specification in column (1) of Table 1. His estimates are the same as the coefficient of 0.046 that we report in estimates based on our larger sample of plants that are new between 1993 and 1997.

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[12] They warn against concluding that higher gross returns mean that plants are under-investing in information technology. Most studies do not adjust for the high obsolescence rate of information technology capital, which lowers net returns. Also, total investment in information technology may be understated because most studies measure only computer hardware, but not related labor or software, or costs of co-invention, such as re-engineering business processes to take advantage of the new information technology.

[13] Both Dedrick (2003) and Stiroh (2002) attribute the failure of early micro data studies to find a relationship to inadequate data with small sample sizes.

While we are reassured by this empirical regularity, we do not make overly much of it. The estimates in Stiroh's analysis may not be adjusted for the high obsolescence rate of computers, the well-known continuing decline in computer prices, or co-invention. Our estimates are for the specific sample for which our data have reasonable proxies, plants that are new in 1997. While we obtain similar results for a larger sample of plants that are new since 1992 (0.117 vs. 0.126), we note that both these estimates far exceed the coefficient estimates for the full sample of plants that report computer investment (0.004), or the network coefficient for the full sample of plants, omitting computer investment (0.037). It also is subject to other biases whose net effects may be of any sign. There is some downwards bias because computer prices continue to fall at a roughly 30 percent annual rate of decline, so the plant's computer investment in 2000 buys much more computer input than the same dollar investment would have bought even in 1999. We assume this price decline affects all plants in the CNUS equally. There is an upwards bias in our estimates, as in the estimates in Stiroh (2002), because we do not measure co-invention. Co-invention is estimated to equal roughly the cost of the hardware and peripheral equipment investment over the life of the investment, so omitting it understates computer inputs.

Our findings also are consistent with a relatively new literature in plant- or firm-level research conducted in other countries and summarized in Pilat (2004). Many studies cited there find positive relationships between information technology and productivity. Several of those studies also find positive relationships between using computer networks and productivity (e.g., Baldwin and Sabourin (2001) for Canada; Bartlesman *et al.* (1996) for the Netherlands; and Clayton *et al.* (2004) for the United Kingdom). Recent research by Motohashi (2003) finds separate positive effects of computer expenditures and computer networks in Japan during the 1990 – 2001 period, with larger effects in more recent years, but also with much heterogeneity in those effects over time and across industries. Many of these new plant- and firm-level studies conclude that computers are not the only factors contributing to productivity. They find important roles for complementary inputs and investments, such as organizational capital, worker skills, and innovation. [14]

[14] Recent research for the United States using detailed firm-level investment in computers, communications equipment, software, and other capital goods, finds that many components of investment, including information technology investments, are related to productivity (Wilson 2004).

While our coefficient estimates for the computer and total capital variables are consistent with the literature, we note again that our computer and total capital variables are proxies for the desired capital input measures. It is difficult to interpret coefficients of these proxy variables as the theoretically specified marginal products of computer and total capital.

Stiroh (2002) concludes that information technology matters, but the wide variation in empirical estimates means that much "depends on the details of the estimation" and "one must be careful about putting too much weight on any given estimates." We agree. Our results reported in this paper and the several specifications reported in our previous research show that theory, specification, and measurement issues matter. Our conclusions also are consistent with the empirical micro literature: computer inputs and computer networks are related to plant-level productivity.

### C. Important Data Gaps and Implications for Data Collections

The new computer network and computer investment variables narrow important gaps in the data we need to understand how information technology affects plant-level productivity. The plant- or firm-level data needed to address the effect of computer networks seldom existed until very recently. These are among the important data gaps that were identified in reviews of the data needed to understand the emerging electronic economy, e.g., Atrostic, Gates, and Jarmin (2000), and Haltiwanger and Jarmin (1999), and that some recent data initiatives address (Mesenbourg 2001).

Early studies lacked large representative national samples collected by official statistical organizations. For example, Dedrick *et al.* report that Barua (1995) draws on 60 business units in 20 U.S. companies. Similarly, Brynjolfsson and Hitt (2000, 2000, and 2003) analyze between 500 and 600 firms for which they combine information from a private database on the firms' computer capital stock with public information on other inputs and financial variables from Compustat.

Larger samples of roughly 38,000 plants became available in the 1988 and 1993 Surveys of Manufacturing Technology (SMT) for the U.S., but were limited to five two-digit SIC industries. Also, while the SMT collected data on the use of a number of technologies, Doms, Dunne, and Troske (1997) stress that they are process and control technologies, and not measures based directly on the use of computers.

The network data in the 1999 CNUS and the 2000 ASM provide critical new data. However, they only provide it for one period. We have enough data to create instruments for the network variable and estimate the 2SLS productivity regression reported in Table 3. But we cannot use panel data techniques to address many standard plant-level measurement issues, including unobserved heterogeneity beyond those input and plant characteristics we control for, such as managerial ability. Nor can we address sources of heterogeneity that are specific to studies of information technology and computers, such as reorganization of work processes or other measures of organizational capital, because such data are not collected in our sources. Long-standing data gaps, such as the absence of information on worker occupation and skills, mean that we cannot control for differences among plants in worker quality. Nor can we investigate how the presence of computers and computer networks affect the dynamics of plant performance.

Some of the largest data gaps affecting our analysis for the manufacturing sector will be addressed in the 2002 Economic Census. Data will be collected on both the book values of assets and capital expenditures, with separate information on expenditures on computer equipment and peripherals. In addition, beginning with data for 2003, the Annual Capital Expenditures Survey (ACES) will collect information on both capitalized and expensed expenditures on information and communications technology structures, and equipment, including computer software. However, ACES is collected at the company level, so neither totals nor separate detail for expenditures on these information technology expenditures will be available at the plant level.

## VI. Conclusions

We use new data on computer networks and computer investment to estimate a production function in which both computer networks and computer input are incorporated as separate variables. We find that both have positive and significant relationships with plant-level labor productivity in U.S. manufacturing. This finding suggests that computer networks are a new technology that shifts the production function, distinct from the productive effect of computer inputs in the production process. We also show the empirical importance of having good proxies not just for the computer network and computer inputs variables of interest, but also for total capital inputs.  When we do not, we would conclude that, while computer networks may not be pencils, they are merely computers.

New data raise the level in the statistical glass, but also raise our expectations for the questions we can answer, without enabling us to address all them (Griliches 1994).  The statistical glass nevertheless is filled higher for U.S. manufacturing than for other sectors.  Data on variables critical to this analysis, such as computer networks, computer investment, book value of capital, and other inputs, such as materials, seldom exist in official U.S. data collections for sectors outside of manufacturing.  The impacts of computer inputs and computer networks remain hard to measure, and their measurement is important.

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**Table 1. Labor Productivity OLS Regression Results:**
**Plants New in 1997**

**Dependent Variable**: Labor Productivity
(T-statistics in parentheses)

| Independent Variables | Plants with Positive Computer Investment in 2000 — New in 1997 (1) | (2) | (3) | All Plants (4) |
|---|---|---|---|---|
| **Intercept** | **3.769 (32.63)** | **3.051 (32.36)** | **3.266 (38.00)** | **2.949 (106.03)** |
| **CNET** | **.117 (2.12)** | **.136 (2.44)** | **(--)** | **.004 (0.25)** |
| **Log ($K_{nc}$/L)** | **.086 (6.02)** | **.093 (6.42)** | **.088 (6.13)** | **.098 (26.92)** |
| **Log ($K_c$/L)** | **.050 (4.36)** | **(---)** | **.052 (4.53)** | **.0478 (16.03)** |
| **Log (M/L)** | **.409 (28.00)** | **.422 (29.15)** | **.409 (27.96)** | **.478 (121.97)** |
| **MIX** | **.040 (1.69)** | **.061 (2.64)** | **.044 (1.85)** | **0.04 (7.08)** |
| **MULTI** | **.161 4.81)** | **.155 (4.59)** | **.167 (5.00)** | **.102 (11.45)** |
| **Plant Size** | **Yes** | **Yes** | **Yes** | **Yes** |
| **Industry (3-digit NAICS)** | **Yes** | **Yes** | **Yes** | **Yes** |
| **$R^2$** | **.655** | **.647** | **.653** | **.740** |
| **Number of Plants** | **849** | **849** | **849** | **12,386** |

Notation in the table is the same as in the estimating equation (4).

**$K_{nc}$/L,** non-computer capital input in 1999**,** is proxied by **K/L97,** the book value of total capital in 1997, divided by 1997 employment.

**$K_c$/L,** computer capital input in 1999, is proxied by **$K_{c2000}$/L**, computer investment in 2000 divided by employment in 1999.

All other variables are measured in 1999.

**Table 2. Labor Productivity OLS Regression Results:**
**Plants New Between 1992 and 1997**

**Dependent Variable**: Labor Productivity
(T-statistics in parentheses)

| | **Plants with Positive Computer Investment in 2000** | | | |
|---|---|---|---|---|
| | **New between 1992 and 1997** | | | **All Plants** |
| **Independent Variables** | **(1)** | **(2)** | **(3)** | **(4)** |
| **Intercept** | **3.009 (39.78)** | **2.916 (39.26)** | **3.117 (47.90)** | **2.949 (106.03)** |
| **CNET** | **.126 (2.78)** | **.1510 (3.31)** | **(--)** | **.004 (0.25)** |
| **Log ($K_{nc}$/L)** | **.084 (8.91)** | **.088 (9.28)** | **.085 (9.01)** | **.098 (26.92)** |
| **Log ($K_c$/L)** | **.046 (5.42)** | **(---)** | **.049 (5.71)** | **.0478 (16.03)** |
| **Log (M/L)** | **.456 (43.38)** | **.466 (44.54)** | **.457 (43.34)** | **.478 (121.97)** |
| **MIX** | **.036 (2.13)** | **.057 (3.51)** | **.038 (2.25)** | **0.04 (7.08)** |
| **MULTI** | **.143 (5.71)** | **.137 (5.43)** | **.149 (5.98)** | **.102 (11.45)** |
| **Plant Size** | **Yes** | **Yes** | **Yes** | **Yes** |
| **Industry (3-digit NAICS)** | **Yes** | **Yes** | **Yes** | **Yes** |
| **$R^2$** | **.678** | **.672** | **.665** | **.740** |
| **Number of Plants** | **1,755** | **1,755** | **1,755** | **12,386** |

Notation in the table is the same as in the estimating equation (4).

**$K_{nc}$/L,** non-computer capital input in 1999**,** is proxied by **K/L97,** the book value of total capital in 1997, divided by 1997 employment.

**$K_c$/L,** computer capital input in 1999, is proxied by **$K_{c2000}$/L**, computer investment in 2000, divided by employment in 1999.
All other variables are measured in 1999.

Table 3. Labor Productivity OLS and Two-Stage Regressions:
Plants of All Ages

**Dependent Variable**: Labor Productivity
(T-statistics in parentheses)

| | All CNUS Plants[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS Estimates | | | | Two-stage Estimates | | | |
| **Independent Variables** | (1) | | (2)[2] | | Standard[2] (3) | | Corrected errors[2] (4) | |
| Intercept | 2.948** | (114.95) | 2.92** | (90.85) | 2.362** | (17.23) | 2.363** | (14.68) |
| CNET | 0.037** | (3.00) | 0.038** | (2.76) | ( -- )[3] | ( -- ) | ( -- )[3] | ( -- ) |
| Pr (CNET) | ( -- ) | ( -- ) | ( -- ) | ( -- ) | 0.669** | (4.39) | 0.669** | (3.88) |
| Log (K/L) | 0.078** | (24.19) | 0.083** | (22.42) | 0.082** | (22.10) | 0.082** | (17.52) |
| Log (M/L) | 0.451** | (118.96) | 0.458** | (105.21) | 0.459** | (105.39) | 0.459** | (52.21) |
| Log (L) | -0.005+ | (1.78) | -0.004* | (-1.25) | -0.003 | (-0.94) | -0.003 | (-0.082) |
| Log (RLP92) | 0.276** | (32.80) | 0.277** | (29.91) | 0.289** | (29.86) | 0.289** | (21.47) |
| Log (MIX) | 0.035** | (7.25) | 0.032** | (5.83) | 0.034** | (6.27) | 0.040** | (2.74) |
| MULTI | 0.088** | (10.04) | 0.082 | (8.55) | 0.04** | (2.85) | 0.0482** | (3.63) |
| New | 0.203** | (7.15) | ( -- ) | ( -- ) | ( -- ) | ( -- ) | ( -- ) | ( -- ) |
| New x Interactions with Inputs Above | Yes | | Yes | | Yes | | Yes | |
| Industry (3-digit NAICS) | Yes | | Yes | | Yes | | Yes | |
| | | | | | | | | |
| $R^2$ | 0.8133 | | 0.7811 | | 0.7724 | | 0.7819 | |
| Number of Plants | 29,840 | | 10,496 | | 10,496 | | 10,496 | |

** significant at the 1% level
* significant at the 5% level
\+ significant at the 10% level

"L" is employment at the plant
RLP92 is the plant's labor productivity in 1992 (1997 for plants new in 1997), relative to its 4-digit SIC industry

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[1] All coefficients are reported in Atrostic and Nguyen 2004.
[2] The number of observations in columns (2), (3), and (4) is smaller than that in column (1) for several reasons. Estimating the probit in the first stage of the two-stage estimates reported in columns (3) and (4) required variables from prior periods that are not used in the OLS estimates. One of these variables, computer expenditures, is reported by only about half of all plants. Additionally, many plants are new since the prior period, 1992. The OLS regression reported in column (2) uses the same reduced sample that is used in the two-stage estimates.
[3] Evaluating the coefficient of the predicted probability at a point consistent with our data yields an estimated network effect of 7.2 percent. This estimated network effect is higher than the OLS estimate of 3.9 percent from the coefficients in column (2).

“New” is a zero – one dummy variable equal to one for plants new since 1997
K /L, total capital input in 1999, is proxied by K/L97, the book value of total capital in 1997.
Other variables defined as in Tables 1 and 2.

## Appendix: Data and Empirical Specification of Variables

### Data

The 1999 Annual Survey of Manufactures Computer Network Use Supplement was mailed to the plants in the ASM sample in mid-2000. The supplement asked about the presence of computer networks, and the kind of network (EDI, Internet, both). It also collected information about manufacturers' e-commerce activities and use of e-business processes. The questionnaire asked if the plant allowed online ordering and the percentage of total shipments that were ordered online. Information on online purchases was also asked. In addition, information was collected about the plant's current and planned use of about 25 business processes conducted over computer network (such as procurement, payroll, inventory, etc., "e-business processes") and the extent to which the plant shared information online with vendors, customers, and other plants within the company.

The Annual Survey of Manufactures (ASM) is designed to produce estimates for the manufacturing sector of the economy. The manufacturing universe consists of approximately 365,000 plants. Data are collected annually from a probability sample of approximately 50,000 of the 200,000 manufacturing plants with five or more employees. Data for the remaining 165,000 plants with fewer than five employees are imputed using information obtained from administrative sources. Approximately 83 percent of the plants responded to this supplement. All CNUS data are on the NAICS basis. Because the data are only from respondents to the CNUS, and are not weighted (see the discussion in www.census.gov/estats), our results may apply only to responding plants. We note, however, that the plants responding to the CNUS account for a substantial share of the U.S. manufacturing employment and output (about 50 to 60 percent) represented in the ASM.

### Variables

- *Capital ($K_T$):* Data on capital services are the appropriate measure for production function estimation and productivity analysis. Because such data are not available at the micro level, we use book values of gross capital stocks (including buildings and machinery assets) collected in the 1997 CM as a proxy for K. We use 1997 data on capital intensity (K/L) because data on total capital stock are collected in the 1997 Economic Census but not in the ASM. Although we recognize that these data have limitations as measures of capital services, it is widely recognized that it is difficult to handle these problems in cross-sectional analysis. We therefore follow many previous studies (e.g., McGuckin *et al.*, 1998 and Greenan, Mairesse, and Topiol-Bensaid (2001)) and use book values of capital as a proxy for capital input, K. This implies that services are proportional to the book value of capital. This assumption is made more reasonable by the controls for plant characteristics in our regressions.

- *Computer Investment ($I_C$):* is computer investment as reported in the 2000 ASM.
- *Materials (M):* are the sum of values of materials and parts, values of energy consumed (including electricity and fuels) and values of contract work.
- *Skill Mix (MIX)*. This variable is defined as the number of non-production workers (OW) divided by total employment (TE) 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.[4]

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[4] 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 higher ratios of non-production to total workers. Doms, Dunne, and Troske (1997) find that plants that adopt new technologies have more skilled workforces both before and after adoption. As with many other plant-level studies, we use 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).

However, some production workers are in highly skilled occupations, and some non-production workers are in relatively less skilled jobs such as janitors, and the literature is scarcely unanimous that the nonproduction

• *SIZE*: Plant size is specified as a standard series of six dummy variables. About 30 percent of the plants in our core CNUS sample have 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.

• *Multi-unit firms' plants (MULTI)*: Many manufacturing plants are part of multi-unit firms, so employment size alone is an inadequate indicator of available resources, managerial expertise, and scale. We construct a dummy variable, "MULTI," 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 multi-unit firm.

• *Industries* (*IND)* : 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 basic empirical model specifications to capture industry-specific effects on plant-level labor productivity.

(1)

labor share is a measure of skill (e.g., Dunne, Haltiwanger and Troske (1997) and Berman, Bound, and Griliches (1994). We follow Dunne *et al.* (2000) in both using this measure and being cautious in interpreting it as an indicator of skill.

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