Economics Program Working Paper Series

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April 6, 2000

EPWP #00 - 03

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Do Computers Make Output Harder to Measure?

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Abstract

In recent years, U.S. productivity growth accelerated sharply in manufacturing, but has remained sluggish in the most computer-intensive service industries. This paper explores the possibility that information technology is generating output that is increasingly hard to measure in non-manufacturing industries, which contributes to the divergence in industry productivity growth rates. Our results suggest that measurement error in 13 computer-intensive, non-manufacturing industries increased between 0.74 and 1.57 percentage points per year in the 1990s, which understates annual aggregate productivity growth by 0.10 to 0.20 percentage points in the 1990s. This adds to an estimated 0.22 to 0.30 percentage point error from the increasing share of aggregate output in these hard-to-measure industries. Thus, increasing measurement problems may understate aggregate productivity growth by an additional 0.32 to 0.50 percentage points per year in the 1990s and play an important role in understanding recent productivity trends at the industry level.

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The authors thank seminar participants at The Conference Board and The Federal Reserve Bank of New York and Al Link (the Editor) for helpful comments on an earlier draft. Dave Fiore and Mike Fort provided excellent research assistance. This paper reflects the views of the authors only and does not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System.

I. Introduction

It is well known that U.S. labor productivity growth slowed considerably after 1973 relative to the immediate post-war period: 3.3% per year for 1949-73 compared to 1.2% from 1973-90. More recently, labor productivity growth recovered slightly to 1.3% per year for 1990-96 and then more dramatically to 2.0% in 1997 and 1998 (BLS (1999a, 1999b)).[1] This acceleration in productivity growth has surprised forecasters, and some commentators now see a "new economy" in which information technology and globalization are finally driving economic growth and productivity.[2]

This chorus of commentary on the new economy is in sharp contrast to the "productivity paradox" debate that followed Robert Solow's famous 1987 quip, "You can see the computer age everywhere but in the productivity statistics." Early research on the productivity impact of computers was often disappointing and only recently has a consensus emerged that computers have an important impact. Jorgenson and Stiroh (2000) and Oliner and Sichel (2000), for example, report a large increase in the growth contribution of computer equipment in the late 1990s; Brynjolfsson and Yang (1996) summarize strong firm and industry results.

Despite these encouraging findings, a closer look at industry-level data suggests that a puzzle remains. Dean (1999) reports that annual labor productivity growth for the entire business sector increased to 1.4% in the 1990s, while labor productivity growth in manufacturing accelerated to 3.7%. This implies little productivity growth for the non-manufacturing portion of the economy. Similarly, Corrado and Slifman (1999) and Gullickson and Harper (1999) point to a widening divergence in productivity growth between manufacturing and non-manufacturing industries.

This divergence is particularly puzzling given the anecdotal evidence of major innovations and quality change in service industries and the well-documented fact that high-tech investment is heavily concentrated in non-manufacturing industries like banking and business services, e.g., Stiroh (1998) and Triplett (1999). Moreover, McGuckin and Stiroh (1998) report

[1]These data are from before the "Benchmark Revision" of the U.S. National Income and Product Accounts, which were released by the Bureau of Economic Analysis in October 1999. This revision increased growth rates of real output and productivity. To be consistent with the earlier, unrevised industry data that is currently available, we still report the earlier aggregate productivity estimates.

that the most computer-intensive industries outside of manufacturing show relatively weak productivity growth in the 1990s. More recently, Gordon (1999) claims all of the productivity revival in recent years is due to three factors – methodological changes to price deflators, normal pro-cyclical productivity gains, and productivity growth in the production of computers – and that there is no real acceleration of productivity in the rest of the economy. These results imply that the recent aggregate productivity gains were achieved in spite of the poor productivity performance in the most computer-intensive service industries.

This combination of rapid computer investment and slow productivity growth outside of manufacturing is striking and, some would say, implausible. One possible resolution is that output, and therefore productivity, is simply not being measured correctly in these industries. Baily and Gordon (1988) and Griliches (1994), for example, speculate that measurement problems within services contribute to the productivity paradox and Triplett (1999) observes computers are highly concentrated in industries where output is particularly hard to measure, like finance, business services, and wholesale trade. The U.S. Bureau of Labor Statistics (BLS) recently addressed the mismeasurement issue and Dean (1999) concludes that recent BLS studies suggest important measurement problems "may be leading to underestimation of productivity growth.[3]" Unfortunately, Dean (1999) also concludes that BLS has no basis for determining the extent of the underestimation.

The primary goal of this paper is to provide an estimate of the increased measurement error in certain non-manufacturing industries and to quantify the aggregate importance. We estimate a range of increased measurement error from a top-down comparison of productivity growth rates across different industries and periods, and then perform a thought experiment similar to Corrado and Slifman (1999) and Gullickson and Harper (1999) to the gauge aggregate importance. By comparing productivity growth across industries and over time, one can get a sense of where measurement errors may be increasing.

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[2]There is a whole range of additional characteristics that define the so-called new economy. For example, the near record economic expansion of the 1990s has featured the surprising combination of low unemployment rates and stable prices. See Stiroh (1999a) for a summary of alternative new economy views.

[3]The adequacy of economic statistics is a matter of long-standing debate. Economists who puzzled over the productivity slowdown that began in the early 1970s viewed measurement error as one candidate for explaining it. Most of this debate has centered on the problems with price deflators. Although the BLS has taken numerous steps to improve measurement of price change, with more planned, the adequacy of deflators remains an issue.

To estimate the aggregate impact in the U.S. economy, we build on Sichel (1997), who outlines an insightful decomposition of the measurement gap – true output growth rate less a measurement error term – into two terms.[4] Sichel (1997) concentrates on a "between effect" that captures the aggregate impact of the growing share of hard-to-measure industries, while we focus on a "within effect," which measures the aggregate impact of increased measurement error within those sectors. In particular, we look at the role of computers and information technology as a source of increased measurement error within computer-intensive, non-manufacturing industries.

The analysis is undertaken in three steps. First, we quantify the variation in computer intensity across industries, both in manufacturing and non-manufacturing. We then estimate the impact of computers in manufacturing, where we believe output and productivity to be better measured. Since manufacturing output measurements are more likely to be accurate than those in the service sector, we have a natural metric for quantifying the within effect. Finally, we determine a range of possible increases in measurement error in the non-manufacturing industries and estimate the aggregate impact.

The results suggest that increasing measurement problems contribute to the growing divergence in industry productivity and are an important, although not dominant, part of the productivity story. After identifying 13 non-manufacturing industries that use computers intensively, we estimate that the increased bias in measured productivity growth was between 0.74 and 1.57% in the 1990s. Since these industries produced less than one-seventh of GDP, this translates to an aggregate impact via the within effect of between 0.10 and 0.20 percentage points. These industries are also growing in output share, however, so there is an additional 0.22 to 0.30 percentage point understatement from the between effect. While this by no means implies that measurement error is the whole answer, the combined impact of 0.32 to 0.50 percentage points per year suggests that increasing measurement error is an important issue.

II. Measurement Error and Productivity Growth

The widespread U.S. productivity slowdown has generated an enormous literature and a large number of potential explanations. In an important paper, Baily and Gordon (1988) raise

[4]Note that measurement error in this context might be more accurately described as a bias since it is assumed that output growth is being systematically understated.

the question of whether the slowdown was real or if measurement problems were responsible. They emphasized two ways that measurement problems impact aggregate productivity estimates – either the share of hard-to-measure commodities must increase or unmeasured output and quality change must increase (pg. 359). Baily and Gordon also raise the question that the computer revolution may be making output harder to measure, although they conclude measurement error explains only a small fraction of the productivity slowdown.

More recently, Griliches (1994) revisits the issue in his 1994 Presidential Address to the American Economic Association by speculating that increased measurement error may be contributing to the slow productivity recovery in the 1980s and early 1990s. Griliches emphasizes that the share of output in "reasonably measurable" sectors has declined from about one-half to one-third. Since output has always been hard to measure in the other sectors, he argues, reallocation of resources contributes to aggregate measurement problems as the hard-to-measure sectors grow. Griliches also suggests that measurement problems were worsening within these sectors and points to changes in the way banks and airlines operate and the increased, but unmeasured, consumer convenience associated with ATMs.

Building on these observations, Sichel (1997) presents a two-sector decomposition to quantify the aggregate impact of changes in measurement problems:

$$(1)\quad \begin{matrix} \textit{Aggregate Change in} \\ \textit{Measurement Error} \end{matrix} = \begin{bmatrix} \textit{Between} \\ \textit{Effect} \end{bmatrix} + \begin{bmatrix} \textit{Within} \\ \textit{Effect} \end{bmatrix}$$

where the "between effect" captures the aggregate impact from a shift toward the hard-to-measure sector, and the "within effect" captures worsening measurement problems within the hard-to-measure sector. Aggregate measurement error, therefore, can increase if either the hard-to-measure sector becomes larger or if it becomes even harder to measure.

Algebraically, Sichel's decomposition can be expressed as:

$$(2)\quad d(\Delta u) = \left[d(s_1)\cdot\Delta u_1 + d(1-s_1)\cdot\Delta u_2\right] + \left[s_1\cdot d(\Delta u_1) + (1-s_1)\cdot d(\Delta u_2)\right]$$

u is measurement error in the subscripted sector, *d* is a difference in a variable, *D* is a growth rate, and *s* is the share of the subscripted sector in total output

The first bracket of Equation (2) measures the "between effect" from a shift in share between sectors. If sector 1 is the hard-to-measure sector, then $d(s_1)\cdot Du_1$ represents the increase in aggregate measurement error as the hard-to-measure sector grows in relative size. Sichel (1997) estimates that the change in the industry output share is $d(s_1)=0.094$ when 1980-90 is compared to 1952-70 and assumes that measurement error was Du_1=2.4%.[5] Thus, Sichel concludes the impact of this reallocation of output to hard-to-measure sectors is small – only 0.23 percentage points and makes mismeasurement an improbable explanation. In his comment, however, Griliches (1997) argues that measurement problems are not the only explanation for the productivity slowdown and that, depending on the comparison, 0.23 is not a negligible effect.

The second bracket measures the "within effect" due to increased measurement error within the hard-to-measure sector. Holding relative shares fixed, aggregate measurement error increases if measurement errors become larger in the hard-to-measure sectors. Relying on Baily and Gordon (1988), who argue that increases in measurement error are unlikely to have had a large effect on measured output, Sichel (1997) does not quantify this second channel.[6] A primary goal of this paper is to quantify the within effect.

(a) Quantifying the Impact of Mismeasurement

Our approach expands the decomposition in Sichel (1997) to include four groups of industries and quantifies the magnitude of the "within effect" from increased measurement error in certain industries. In particular, rather than looking at only measurable vs. hard-to-measure sectors as above, we create four industry groups: 1) manufacturing industries that use computers, 2) manufacturing industries that do not use computers, 3) non-manufacturing industries that use computers, and 4) non-manufacturing industries that do not use computers. By comparing changes in relative productivity growth across the two groups of manufacturing industries where output is easier to measure, we can infer the relative productivity gains associated with computers. This estimated change then proxies for increased measurement error in the hard-to-measure non-manufacturing industries that use computers.

Our approach relies on two, critical identifying assumptions. First, we assume that productivity is well measured in all manufacturing industries, regardless of whether they use

[5]The shares represent industry gross product originating shares and the assumed 2.4% measurement error represents a "plausible upper bound" estimate based on Popkin (1992).
[6]An important issue here is that many of the hard-to-measure industries produce primarily for intermediate sales and not for final demand. Baily and Gordon (1988) argue that those sectors where increased measurement might be relevant accounted for a very small portion of final demand. Triplett (1999) also concludes that the majority of computer investment in hard-to measure service industries is in intermediate industry categories. We address this in the empirical section.

computers.[7] This allows us to estimate the productivity impact of computers. Second, we assume that the marginal impact of computers is the same in non-manufacturing as it is in manufacturing. This allows us to estimate the potential increase in measurement error in computer-using, non-manufacturing industries. Estimating the impact of computers, however, is a difficult empirical task and we provide a range rather than a precise point estimate. Before proceeding to the empirical section, it is useful to discuss why output measurement problems may be worsening in computer-using, non-manufacturing industries.

(b) Are Measurement Problems Becoming Worse in Services?

A wide variety of factors cause output to be hard to measure in services industries. While different analysts emphasize different factors, e.g., definitional problems, deflator issues, data constraints, etc., there is widespread agreement that non-manufacturing output has always been more difficult to measure than manufacturing output.[8]

It is less clear, however, that these measurement problems have changed over time or if any change is specifically a result of computer investment. On one hand, data and statistical techniques are clearly improving,[9] but information technology may be changing the nature of output in ways that are fundamentally more difficult to measure. A complete resolution would require an industry-by-industry analysis of the outputs, data, and statistical methods used to create the output and productivity indexes. Rather than begin such an ambitious task, we follow the top down approach of Corrado and Slifman (1999), Dean (1999), and Gullickson and Harper (1999) and infer an increase in measurement problems from the growing divergence in productivity growth between industries.

Figure 1 reports official BLS labor productivity (output per hour) growth from Dean (1999) for the business sector and the manufacturing sector for various sub-periods from 1949 to 1998. In the 25 years in the immediate post-war period, business sector productivity growth exceeded manufacturing, which implies that non-manufacturing productivity grew faster than manufacturing productivity. This trend reversed during the slowdown in the 1970s. In the 1990s this divergence accelerated with manufacturing productivity growth nearly three times as fast as

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[7]If manufacturing productivity growth associated with computers is also understated, this only reinforces our estimate since our benchmark will be too low.
[8]See Griliches (1994, 1992) and Dean (1999) for details on common explanations.
[9]Both Dean (1999) and Triplett (1999) note that there have been improvements in the statistics for many industries and that measurement error may have decreased in some industries.

business sector productivity growth. Clearly something has changed. Either non-manufacturing productivity growth has truly slowed relative to both the earlier period and relative to manufacturing or increases in measurement problems are masking true productivity trends.

This widening divergence has been emphasized in several recent studies. Gullickson and Harper (1999) report negative total factor productivity growth for many service industries over the last 15 years. Using different data from the national accounts, Corrado and Slifman (1999) made a similar observation regarding labor productivity. Both papers find negative productivity growth over long time periods to be unreasonable and undertake "thought experiments" where the negative growth rates are replaced by zero productivity growth. McGuckin and Stiroh (1998) report that labor productivity growth accelerated for manufacturing industries that used computers most intensively, but not for computer-intensive non-manufacturing industries.

In an excellent overview of the measurement issue, Dean (1999) concludes that these observed negative trends are implausible and are indicative of worsening measurement problems in the underlying data, most likely the real output data and not the input series. It is important to emphasize that this conclusion reflects the fact that non-manufacturing productivity growth has slowed in two ways – relative to both manufacturing and relative to the earlier periods. One reasonable explanation for both trends is that measurement problems are becoming more severe in non-manufacturing industries.

(c) Are Computers the Problem?

Even if one believes that measurement problems are becoming more severe outside of manufacturing, it is not clear that information technology is responsible. While we do not prove that computers are playing a causal role, an accumulation of anecdotal and circumstantial evidence is building that suggests computers are changing the composition of output in ways that makes accurate productivity estimates more difficult.

Computer technology appears closely linked to several aspects of conventional measurement problems such as quality change, product variation, innovation, and new products. Baily and Gordon (1988) first raise this issue by noting that many valuable computer-related services are not captured in the official data. They provide a list of examples, e.g., changes in airline ticketing, increased consumer convenience associated with better inventory control, on-line banking, mutual fund diversification, and better information flows from retailers, but conclude that the relatively small final demand share of the most affected industries makes the aggregate impact small.

More recently, Siegel (1997) argues that computers worsen errors in the measurement of productivity since computers create quality change that is not accounted for in the price statistics. Using data for 450 4-digit manufacturing industries from 1958-89, he finds that computers are correlated with measurement error and speculates that the effect could be even stronger in service industries. Diewert and Fox (1999) argued that information technology increases the variety of products and allows other quality improvements that are hard to measure, although Triplett (1999) disagrees with this assessment. Berndt and Morrison (1995) speculate that increased quality change is a likely explanation for their surprising finding of a negative correlation between computer intensity and productivity in U.S. manufacturing industries in the 1980s. The empirical results of Lehr and Lichtenberg (1997, pg. 19), who find a peak impact of computers in 1986, suggest that measurement problems may have worsened in recent years.

On a conceptual level, the well-known problems associated with output measurement in the service sector may be particularly true for many of the most computer-intensive industries like trade, depository institutions, insurance, and personal and business services. Even where there is a quantifiable representation of the output of the industry through margins, number of transactions, or revenues, the resulting output measure is often inadequate. This is because an estimate of what accrues to the seller or supplier of the service does not provide an adequate yardstick for measuring the services received since the consumer is an important producer of the output.[10]

Perhaps the most important problem is that the dimensionality of the output received in many of the computer-intensive service sectors is multifaceted, varying with the time and effort the individual consumer invests and also with the complementary resources available. This is true in such areas as distribution, legal, health, and business services, entertainment, and security investments. Moreover, the extent of these investments and the quality of the delivery and information received are rapidly changing over time in large measure due to computers. For example, better inventory control allows retail stores to increase the range of items carried and computerized checkouts – an important part of the inventory system – make shopping quicker.

[10]See Hill (1977), Sherwood (1994), and Griliches (1992).

One reason why micro-data studies, like those surveyed by Brynjolfsson and Yang (1996), are much more likely to observe productivity gains is that these studies are able to measure output along several dimensions or margins. Thus, the various anecdotes that rely on studies of specific industries often find much higher productivity than that in the official statistics. For example, Popkin (1992) finds productivity seriously understated in all of the computer-using industries he examined, e.g., insurance carriers, grocery stores, banking, legal services, and printing and publishing.

As a concrete example, Berger and Mester (1999) report that bank profit productivity has accelerated in the 1990s, while cost productivity worsened. They conclude that banks now offer a wider range of products and provide additional consumer convenience through ATM networks, increased branching, and on-line services that raise costs but improve profits even more. They emphasize the empirical difficulties in measuring "these additional services or higher service quality, which are difficult to control for in cost or profit functions (pg. 34)." Similarly, Stiroh (1999b) finds that bank holding company productivity has increased and that one must account for non-traditional bank activities like financial derivatives and other off-balance sheet items in order to correctly measure efficiency of the largest firms. In both cases, measurement problems seem to be increasing and may be associated with computers.

Another potential link between computers and measured productivity may be through output definition problems. In some industries, output is estimated according to observed profit or interest margins. For a variety of reasons – deregulation, globalization, and competition, all closely linked to rapid dissemination of information via information technology – these margins have been falling, which is leading to estimates of output growth below their actual levels.

As final, and not very scientific, evidence, we list several examples suggesting measurement problems are worsening due to information technology. In financial services, new products like derivative contracts are impossible without high-tech computer equipment and some of the benefits, e.g., risk reduction and diversification, are not easily quantified. Computers may also improve efficiency via loan scoring and data-warehousing applications. Auto repair services now rely on computer-aided diagnostics to improve the quality and timeliness of auto repairs. Similarly, high-tech equipment is an important part of medical diagnostic procedures. In terms of joint production, ATMs and on-line banking allow consumers increased convenience, a service from the banking sector that requires inputs from the consumer.

Airline reservation systems and on-line services now provide an enormous increase in the amount of information available to consumers, which allows more informed choices. While not representative by any means, this list highlights the reasons why it appears at least plausible that computers may be making output harder to measure in non-manufacturing industries.

III. Previous Research on Computers and Productivity

Previous work that examined the impact of computers on productivity typically begins with an extended production function that treats computer or high-tech equipment as a distinct capital input. In general, output depends on various capital and labor inputs, as well as the total factor productivity residual, through the familiar production function: $Y = A \cdot f(K_1, K_2, L)$, where Y is output, L is labor, K_1 is non-computer capital, K_2 is computer capital, and A is total factor productivity (TFP).

Working from this production function, there are two common ways to quantify the impact of computers. Jorgenson and Stiroh (2000, 1999, 1995), Oliner and Sichel (2000, 1994), Haimowitz (1998), and Stiroh (1998) use a "growth accounting" methodology that systematically attributes growth in output to growth in inputs and a TFP residual. This approach is typically implemented at the aggregate or industry level. Alternatively, one could econometrically estimate some version of a production function as in Berndt and Morrison (1995), Brynjolfsson and Hitt (1995), Gera, Gu, and Lee (1999), Lehr and Lichtenberg (1999), Lichtenberg (1995), McGuckin and Stiroh (1999), and Steindel (1992). Morrison (1997) estimates the dual cost function. These econometric papers all use industry or firm-level data.

(a) Computers and Growth Accounting

Growth accounting allocates output growth to the contribution of measured inputs and a contribution from unmeasured factors, i.e., the famous Solow residual. Under standard neoclassical assumptions – all factors are paid their marginal product and all income is paid out to inputs – output growth can be decomposed into the contribution of each type of capital, the contribution of labor, and the total factor productivity residual. An input's contribution depends on its relative share and real growth rate.[11] Alternatively, one can quantify the input contribution

[11] The standard growth accounting equation is $\Delta Y = w_{K1}\Delta K + w_{K2}\Delta K + w_L \Delta L + \Delta A$ where *D* represents a growth rate, *w* is the income share of the subscripted variable, and $w_{K1}+w_{K2}+w_L=1$

to average labor productivity (ALP) by computing the contribution from capital deepening, labor quality, and TFP effects.

After decades of tremendous price declines and massive substitution toward computers, recent aggregate work suggests that computers are making a meaningful contribution to U.S. economic growth. For example, Jorgenson and Stiroh (2000) estimates that computer hardware contributed 0.36 percentage points to private nonfarm business output growth from 1996-98, up from 0.15 for 1990-95. Stiroh (1998) reports growth accounting results for 35 industries through 1991 and finds large substitution towards computers and rapid accumulation in virtually every sector, but little TFP gains in the most computer-intensive sectors.

It should be emphasized that price-induced capital deepening where computers contribute directly to output and labor productivity growth is entirely consistent with standard neoclassical theory. This type of capital deepening, however, does not affect TFP growth. Accumulation of computer capital increases measured TFP growth only if there were some mismeasured capital services from computers or if computers generate a non-traditional impact like production spillovers. There is currently no compelling evidence, however, to suggest that these spillovers are as large as the direct impact.

(b) Econometric Estimates

Many authors have econometrically estimated a production function that explicitly includes computer capital as an input. This literature in extensive and we briefly review only a few representative papers. Lehr and Lichtenberg (1999), for example, assume a Cobb-Douglas specification and compare the log of output to the log of inputs for a cross-section of firms from 1977 to 1993.[12] Lichtenberg (1995) estimates a similar equation with earlier data, and Brynjolfsson and Yang (1996) survey the literature in detail.

Both Lehr and Lichetnberg (1999) and Lichtenberg (1995) report substantial excess returns to computer capital (and labor), although there are methodological questions about the relative rental price calculations and omitted variables. Brynjolfsson and Hitt (1995) use a similar dataset, but a more flexible translog specification, and conclude that firm-specific effects can account for much of the large productivity impact previously attributed to computers.

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[12]A general specification is $Y_t = a + b_0 \ln L_t + b_1 \ln K_{1t} + b_2 \ln K_{2t} + q_T T + q_I I + e$ where T is a series of year dummy variables and I is a series of industry dummy variables (fixed effects) and variables are defined as above.

Surprisingly, Brynjolfsson and Hitt (1995) find no difference in the impact across sectors, e.g., manufacturing vs. non-manufacturing or "measurable" vs. "unmeasurable," although their firm-level sample contains relatively few observations in the unmeasurable service sector. More recent work by Brynjolfsson and Yang (1998), however, suggests that much of these excess returns are actually returns to hard-to-measure inputs like software and organization capital and raise questions about the high excess returns found in earlier studies.

Berndt and Morrison (1995) and Steindel (1992) focus on a labor productivity equation to measure the productivity impact from computers relative to other forms of capital.[13] If computers are more productive than other forms of capital, then an increased share of capital in computers will have a larger productivity impact. Looking at manufacturing industries, these two studies reach strikingly different conclusions. Steindel (1992) finds that high-tech capital formation was a significant factor in manufacturing productivity growth in the 1980s, while Berndt and Morrison (1995) report that high-tech office equipment is negatively correlated with labor productivity within manufacturing. They suggest that quality change and measurement problems may contribute to this surprising finding. Using the cost dual, Morrison (1997) finds rising returns to high-tech investment in the 1990s after relatively low returns in the 1980s.

As a final common specification, Gera, Gu, and Lee (1999) estimate the relationship between ALP growth and capital input growth.[14] Using data for both the U.S. and Canada, Gera et al. report a statistically significant relationship between IT investment and productivity growth. The estimates typically find a higher rate of return on IT investment, which is consistent with economic theory. Since computers depreciate and obsolesce so rapidly, a high rate of return is required to offset the high user cost.

IV. Data Construction and Sources

We use data from several distinct sources to construct measures of industry labor productivity and computer capital intensity. Gross output by industry is obtained from the Employment Projections division of the BLS; gross product originating by industry is from the

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[13]A general specification is $\ln(Y_t / L_t) = a + b_1 \ln(K_{1t} / L_t) + b_2 \ln(K_{2t} / L_t) + q_T T + q_I I + e$. Berndt and Morrison (1995) actually include labor intensity, ln(L/Y) as the dependent variable, but the spirit of the regressions is the same.

Bureau of Economic Analysis (BEA); and capital stock by industry and asset is from the BEA. Since industries in these different datasets are defined at different Standard Industrial Classification (SIC) levels, an important step was to consolidate data to a common level of industry aggregation.

(a) BLS Gross Output

Gross output represents the producer's value of all products and services produced in a given industry as estimated from the Office of Employment Projections at the BLS. Raw data come from a variety of sources including the Census and Annual Survey of Manufacturers, the National Income and Product Accounts, the IRS, and other sources. Output series are benchmarked by BLS to input-output tables produced by BEA. Price data are chain-weighted estimates from more detailed industry classifications and can be estimated from 1958 to 1996 by combining different vintages of this data. Labor data includes both hours worked and employment, but detailed labor is only available from 1978. These data are at the two- or three-digit SIC level for 169 detailed, private industries. Private households are excluded from the subsequent analysis, so only 168 private industries are actually incorporated.

(b) BEA Gross Product Originating

Gross product originating (GPO) represents each industry's contribution to gross domestic product as calculated by BEA. This data, also called value-added, equals gross output less intermediate inputs and thus equal payments to labor and capital. These data include current and chain-weighted constant dollar GPO for 62 detailed private industries. The current dollar GPO is from 1948 to 1996, while the constant dollar GPO is only from 1977-1996. Data on full-time equivalent employees, FTE, is available for the same industries from 1947-1996. The data correspond to Lum and Yuskavage (1997), Lum and Moyer (1998) provide an update, and Yuskavage (1996) describes the data sources and estimation process used by BEA.

(c) BEA Tangible Wealth Survey

Investment and capital stock are estimated by the BEA as part of their Tangible Wealth study (BEA, (1998)). These data include current dollar net capital stocks and corresponding

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[14]For example, one could estimate $\Delta(Y_t / L_t) = a + b_1\Delta(K_{1t} / L_t) + b_2\Delta(K_{2t} / L_t) + q_T T + q_I I + e$. Gera, Gu, and Lee (1999) estimate a specification that has net investment rates and additional explanatory variables, e.g., research and development investment.

chain-weighted quantity indexes for 62 private industries and 57 assets from 1947 to 1996. Details on the estimation and data sources can be found in Katz and Herman (1997) and these data correspond to those reported in the September 1997 *Survey of Current Business*.

(d) Creating Consistent Data

All three datasets report industries based on 1987 SIC codes, but they are at different levels of aggregation. The BLS gross output data, for example, includes data at the three-digit SIC level, while the BEA data is at the one- and two-digit SIC level. The industry data used in this paper, therefore, represent consolidated data, through SIC codes, at the "least common denominator" level. That is, data was aggregated to form the maximum number of detailed industries that had data from all three sources. To focus on the private business economy, we excluded government enterprises, general government, and private households from our industries. Aggregation of output and capital stocks was done with a Divisia quantity index, which has the desired exact aggregation properties, while labor series were simple sums. This procedure resulted in 55 detailed industries that comprise 10 major sectors with data on gross output, gross product originating, and capital stock by asset.

Average labor productivity was defined as the ratio of real gross output to employment. To ensure the longest possible time series, we used employment series on persons engaged in production from the BEA, rather than hours from the BLS.[15] Real gross output is our preferred measure of output since it represents the value of goods and services produced by the industry, rather than just the industry's value-added contribution to GDP. This is a more fundamental measure of production and avoids the artificial construction of real GPO series.

Moreover, the official real GPO series are often estimated from input-based extrapolations and are less reflective of the underlying productivity trends. Dean (1999) emphasizes the use of input data to estimate output as a primary source of bias in real output by industry, e.g., extrapolation techniques based on inputs such as the use of "paid employee hours" to compute the output trends for the largest segment of the banking industry in the official GPO data. Dean (1999) also identifies the use of input price indexes as another key factor in biasing

[15]The different labor series were highly correlated and did not change results for later periods substantially. We used the BEA employment series simply because it represents official data for the full period. As a further robustness check, hours by industry data from Gullickson and Harper (1999) were compared to these data. Again, the series were highly correlated.

productivity growth towards zero in these industries. According to Eldridge (1999), 14% of industry GDP is constructed using input based methods and 78% of this is in services.

To measure the composition of the capital stock, we created several aggregates from the detailed capital stock series. Computers include mainframes, personal computers, direct access storage devices, printers, terminals, tape drives, and other storage devices. Other high-tech equipment includes communications equipment, instruments, and photocopy equipment. Low-tech equipment includes all other producers' durable equipment. Structures include all non-residential structures. Thus, our capital measure excludes residential structures, land, and inventories and includes only fixed, reproducible tangible assets owned by the business sector.

A final issue worth discussing is our focus on average labor productivity (ALP). This is our primary productivity measure since the direct impact of capital accumulation is on ALP via the capital deepening effect in Equation (4). Total factor productivity (TFP) is affected by capital accumulation only if inputs are mismeasured or if there are productivity spillovers. In principle, we could estimate TFP and search for these effects empirically, but calculating TFP is difficult and we did not have the detailed data that are necessary to correctly measure labor and capital quality. Moreover, measuring ALP allows us to avoid a variety of issues relating to decomposing quality-adjusted capital accumulation and embodied technical change.

V. Descriptive Statistics

(a) The Evolution of Computer Intensity

Table 1 shows the evolution of computer capital for major sectors and the detailed industries from 1970 to 1996. These data show rapid accumulation of computers throughout the economy, as documented in the aggregate work of Jorgenson and Stiroh (2000) and Oliner and Sichel (2000), and also wide variation across major sectors and within industries. The private business sector shows an average computer share of the capital stock of 1.8% in 1996, for example, while less than 0.02% of agriculture capital is computers. Table 1 also shows wide variation in the accumulation rates of computers across major sectors, ranging from 8.35% in mining to 28.84% in wholesale trade in the 1990s. These growth rates far exceed the growth in other forms of capital, typically by a factor of 10. A final interesting observation from Table 1 is that the growth in computers was typically fastest in the 1980s. Recent data in the national accounts, however, suggest that this trend may have again reversed as investment in computers exploded in 1997 and 1998 with the widespread growth of Internet applications.

Table 2 compares the distribution of capital within major sectors and detailed industries. Again, there is wide variation in all forms of capital since different industries have fundamentally different production techniques. It is nonetheless interesting to note the wide variety in computer intensity and hi-tech capital intensity both within and across major sectors.

Table 3 presents the distribution of capital in a different way by reporting total computer and hi-tech capital across major sectors. As reported in Triplett (1999) and Stiroh (1998), computers are highly concentrated in service-related sectors with wholesale trade, retail trade, finance insurance and real estate, and services owning over $120 billion dollars of computers, accounting for over 78% of the U.S. business total. Manufacturing, on the other hand, holds only $26 billion or 17%. High-tech capital is not as concentrated since the transportation, communications, and utilities industries hold a large share of communications assets.

Table 4 presents similar data for the ten detailed industries that own the most computer and high-tech equipment. Again, these are primarily service-related industries with only two manufacturing industries – electronics and other electric equipment and industrial machinery and equipment – making the top ten. Business services, which includes software and computer-related services, is the second largest owner of computer equipment with nearly $26 billion of computer capital. Six of the largest computer capital owners overlap with the ten largest high-tech capital owners, but the classifications are not identical.

(b) Trends in Labor Productivity Growth

Table 5 reports growth in labor productivity – defined as real gross output per employee – for major sectors and detailed industries for various sub-periods from 1958 to 1996. The total value of 1996 gross output is also reported as a measure of the relative size of each major sector or detailed industry. The results are consistent with the well-known trends discussed above. Economy-wide productivity was strong prior to 1973, slowed sharply during the 1970s, and then rebounded in the 1990s. As pointed out by Dean (1999), Gullickson and Harper (1999), Corrado and Slifman (1999), and others, the recovery was largely fueled by accelerating productivity growth in manufacturing industries. The service sector, on the other hand, shows negative productivity from 1973 to 1996.[16]

Table 5 also presents productivity growth rate for the detailed industries and the most striking observation is the enormous variation across industries. Within manufacturing, for example, measured productivity fell 0.5% per year in lumber and wood products, but increased 8.7% in electronic and other electric equipment in the 1990s. Likewise, within the service sector, productivity growth rates varied from 3.3% in auto repair to –3.0 in legal services.

VI. Productivity and Computers

This section examines the empirical relationship between computers and productivity growth, with a particular focus on differences between manufacturing and non-manufacturing industries. To identify this relationship, one must first determine the proper indicator of computer-intensity. Absolute capital, relative capital shares, or investment rates are all reasonable indicators, but perhaps the most natural choice is the relative share of computers in total capital. Figure 2 plots the distribution of nominal computer capital as a share of the total capital stock in 1990 for the 55 detailed industries and a cut-off for a "computer-using" industry appears to be around 2%.

Alternatively, one could choose a relative cut-off at one-third, and define the 18 most computer-intensive industries as "computer-using" and remaining 37 industries as "non-computer-using." These 18 computer-using industries all have a computer capital share above 2.4% with a mean share of 5.1% in 1990. In contrast, the non-computer-using industries have a mean share of 0.7%. This one-third cut-off is our primary indicator of computer-use and Table 6 lists the detailed industries broken down across two dimensions – manufacturing/non-manufacturing and computer-using/non-computer-using. The classification system seems reasonable with the industry breakdown consistent with prior expectations. We also use a continuous measure of computer intensity in the following section.

Table 7 reports the productivity growth for various sets of industries in terms of both weighted and unweighted means. Consistent with our basic hypothesis, computers seem to be

[16] These productivity estimates do not accurately reflect economy-wide productivity since they do not adjust for sales of intermediate inputs between industries and sectors. Rather, they are simply aggregate gross output per total labor and are presented to maintain consistency with the other tables. Figure 1, from Dean (1999), provides the official economy-wide productivity estimates.

associated with productivity gains in manufacturing. Manufacturing industries that use computers show a large acceleration of productivity growth from 2.7% for 1958-73 to 4.8% for 1990-96 (unweighted), while other manufacturing industries experienced a slight slowdown from 2.9% to 2.6% (unweighted). Consistent with the idea that output is becoming harder to measure outside of manufacturing, non-manufacturing industries show a continued productivity slowdown in the 1990s. The results using weighted averages, with the beginning of the period labor used as the weight, are even stronger.

(a) Difference in Means

We first perform a statistical test for differences in means of these productivity changes. That is, we compare productivity growth of industries that use computers to those that do not use computers both before and after the widespread diffusion of computers. If computers matter, the rapid investment and capital deepening should lead to a relative acceleration of productivity growth for industries that use computers.

Table 8 reports results simple tests for the equality of the means for various groups of industries. In all cases, the variable in question is the acceleration of productivity growth, either the mean for 1990-96 less 1958-73 or for 1990-96 less 1979-90. We exclude the period 1973-79 due to the deep overall productivity slowdown, which makes interpretation difficult. The computer-using industries are defined as the 18 industries (top one-third) with the largest computer capital share in 1990, which is the beginning of the period in which we are interested.

The results support our hypothesis that computers contribute to measured productivity in manufacturing, but that the impact may not be measured outside of manufacturing. Comparing 1990-96 to 1958-73, the data show a large but insignificant difference in the change in productivity growth between manufacturing and non-manufacturing (p=0.15) and the difference between all computer-using and non-computer-using industries is only marginally significant (p=0.08). A more detailed breakdown across both classifications suggests that manufacturing industries that use computers experienced a significant acceleration of productivity relative to other manufacturing industries (p=0.04), but the difference in non-manufacturing is smaller and not significant (p=0.21). For the later comparison of 1990-96 to 1979-90, the difference in manufacturing is not significant, but change in productivity growth is quite different from non-manufacturing industries, where computer-using industries actually showed a relative decline in productivity growth rates.[17]

While suggestive, this simple analysis is limited since it does not control for other factors that affect productivity growth like total capital accumulation. The next subsection embeds this type of analysis in a regression framework that allows additional explanatory variables.

(b) Difference-in-Difference Estimator

Estimating the impact of computers involves several difficult econometric issues, e.g., there are potential biases from omitted variables and endogeneity issues. One way to avoid some of these problems is a difference-in-difference estimator that compares the relative productivity performance of industries before and after the rapid accumulation of computers, while still controlling for other factors. That is, we want to augment the simple test of the equality of the means with additional explanatory variables.[18]

Before reporting the results, several points about this approach are warranted. First, the parameter of interest is the marginal increase in productivity for computer-using industries relative to other industries. Second, this approach is a "long difference" estimator since we compare productivity growth rates for periods rather than separately for each year. This has the advantage of avoiding difficulties in correctly specifying the appropriate lag structure for capital deepening and smooths the noisy productivity series, but comes at the cost of losing information. Finally, we include overall capital deepening to control for capital effects that impact productivity independently of computer intensity.[19]

We estimate the difference-in-differences estimator separately for manufacturing and non-manufacturing industries under the hypothesis that output and productivity are not well-measured outside of manufacturing. Results are reported in Table 9. The first two columns,

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[17]This is a test of statistical significance based on sampling variation. Our data, however, contains all industries and thus one must interpret the variation more broadly as representative from some underlying distribution of potential industries.

[18]This difference-in-difference approach suggests this regression $\Delta y_t = a + bT + j\,C + gTC + d\Delta k_t + e$. Dy_t is the average growth rate of labor productivity over period t, T is a dummy equal to 0 for the early period of 1958-73 and equal to 1 for the later period of 1990-96, C is a dummy variable set equal to 0 for non-computer-using industries and equal to 1 for computer-using industries, Dk_t is capital deepening, and t is either 1958-73 or 1990-96. In this specification, γ represents the relative productivity acceleration for computer-using industries.

[19]There is also econometric issue since the periods are of different lengths. If one assumes that the annual errors are i.i.d., then averages across different length periods will generate errors in Equation (8) that are heteroskedastic, e.g.,

which do not control for overall capital accumulation and use OLS, show a change of 2.4 percentage points (significant) in manufacturing and 1.7 percentage points (not significant) in non-manufacturing.[20] When capital accumulation controls are included and OLS is used, the marginal impact is 2.3 percentage points (significant) in manufacturing and 1.6 percentage points (not significant) in non-manufacturing. In both cases, there is a significant acceleration of productivity growth for manufacturing industries that use computers intensively relative to manufacturing industries that do not, while the relationship is much weaker and not statistically significant for non-manufacturing industries.

Table 9 also reports estimates using weighted least squares, with beginning of the period labor used as the weight. Weighting industries by relative size is reasonable since the industry classifications are based on the availability of data and are therefore somewhat arbitrary, which makes it natural to give more importance to larger industries. For example, the wholesale trade industry is roughly 130 times as large as the leather industry in 1996. In addition, we are ultimately interested in the aggregate impact of computers, so weighting industries provides a clearer picture of the economy.[21] These weighted results are even stronger than the unweighted results – a 3.0 percentage point impact from computers in manufacturing (the larger computer-intensive industries showed relatively fast productivity acceleration in manufacturing) and a smaller 1.4 percentage point estimated impact in non-manufacturing (the larger computer-intensive industries showed slow productivity acceleration in non-manufacturing).

This analysis provides two important results. First, manufacturing industries that use computers show a significant acceleration of productivity growth relative to manufacturing industries that do not, even after controlling for overall capital accumulation. Second, relative productivity gains from computers are largest in manufacturing. These data suggest the computer impact in manufacturing exceeds the non-manufacturing impact by 0.74 (2.32 less 1.58) to 1.57 (3.00 less 1.43) percentage points.

(c) Production Function Estimates

The preceding results show that industries that use computers intensively experienced a relative acceleration of productivity growth, and that the measured impact is larger in

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the variance will be larger for shorter periods. We correct for this by applying weights equal to the square root of the number of years in each period. See Greene (1990), pg. 290 for details.

[20]Note that these are the same values as tests of means in Table 8 since there are no control variables.

manufacturing. This section provides additional evidence by estimating production functions similar to Berndt and Morrison (1995), Brynjolfsson and Hitt (1995), Lehr and Lichtenberg (1999), Lichtenberg (1995), and Steindel (1992). While we don't use this approach to quantify the measurement bias, these estimates provide support for the idea that computers have a larger measured impact in the manufacturing industries. This approach, which includes computer intensity as a continuous right-hand side variable rather than an indicator variable, also allows us to test the robustness of our somewhat arbitrary computer-use label in the preceding section.

To test the hypothesis that the measured impact of computers is stronger in manufacturing than in non-manufacturing industries, we augment both the production function and the labor productivity regression with a dummy variable that allows the marginal impact of computers to vary between manufacturing and non-manufacturing industries. In both cases, we can then measures the marginal gain in output or productivity associated with increases in computers in manufacturing relative to non-manufacturing industries. Both specifications are estimated via OLS, a fixed effects approach (industry-specific intercepts) to control for omitted variable that are constant over time, and a between effects approach (average across time for each industry) to focus on inter-industry differences. The OLS and fixed effect regressions include year dummy variable. Results are reported in Table 10.

In every specification, the difference in the marginal impact of computers between manufacturing and non-manufacturing industries is positive and statistically significant. As in Lehr and Lichtenberg (1999) and Brynjolfsson and Hitt (1995), adding industry fixed effects reduces, but does not eliminate, the positive impact of computer intensity. For example, after including year and industry effects, a one percentage point change in computers is associated with an insignificant 0.3% decrease in non-manufacturing output and a 1.6% difference in manufacturing. The same patterns emerge if we estimate a production function or a constrained labor productivity relationship.

While regressions of this sort are common in the literature, they must be interpreted cautiously due to the omitted variables and potential endogeneity problems mentioned above.[22] While industry fixed effects can control for omitted variables that are constant over time, but they do not resolve the endogeneity problem. For example, any omitted factor that influences

[21] See Kahn and Lim (1998) and Casselli (1999) for examples of labor weights in industry analyses.
[22] See Griliches and Mairesse (1995) for a discussion of this problem.

both computer investment and output will cause the error term to be correlated to that explanatory variable and lead to a biased estimate. We, however, are not interested in the coefficient per se, but rather the difference between manufacturing and non-manufacturing industries. Since there is no a priori reason to expect the endogeneity problem to be more severe for either set of industries, we conclude from these results that the impact of computer intensity is larger in manufacturing industries without focusing on a specific point estimate.

A second limitation is the use of capital stock as opposed to more appropriate measure of the flow of capital services from the installed stock. While preferred, we did not have access to the detailed data, e.g., ownership structure, tax treatment, capital incomes, etc., that are required for these calculations.[23]

VII. Estimates of the Aggregate Impact of Mismeasurement

This section incorporates the estimated productivity impact of computers into the decomposition of Sichel (1997) to gauge the aggregate impact of increased mismeasurement. As discussed above, this exercise should be viewed as a thought experiment like Corrado and Slifman (1999) and Gullickson and Harper (1999). We assume that increased productivity growth rates in manufacturing in the 1990s partially reflect increased computer intensity and that computer-intensive non-manufacturing industries do not show comparable productivity gains since the data are missing precisely the type of new outputs that computers facilitate. This is in the spirit of Griliches who wondered if " 'the recovery that did not come' may have been the result of increasing measurement problems (Griliches (1997), pg. 371)."

We first estimate the "within effect," $s_1 \cdot d(Du_1)$ in Equation (2) which measures the aggregate impact of increased measurement error in the computer-using, non-manufacturing industries. We then estimate the "between effect," $d(s_1) \cdot Du_1$ in Equation (2), which measures the aggregate impact of an increasing share of these hard-to-measure industries as in Sichel (1997). Finally, the two effects are combined to form an estimate of the total impact of measurement error for the U.S. economy.

(a) Within Effect

Estimating the within effect requires two pieces of information – the original output share of the industries and the increase in measurement error – for the industries in question. As noted above, we limit this analysis to the 13 non-manufacturing, computer-using industries where it appears that measurement problems are most severe and where we have a metric for estimating the bias.

The first piece of information is the share of these industries in total output, s_1. As emphasized by Baily and Gordon (1988) and Sichel (1997), the appropriate industry share depends on final demand produced within an industry. Since GDP is computed from the product side, undermeasurement of an industry's output affects the total only to the extent that final demand is mismeasured. Any other measurement problems reallocate output between industries since the total is already fixed. Sichel (1997), however, uses industry output shares on the grounds that these are similar to final demand shares.

To estimate final demand shares by industry, we used the Input-Output tables from 1977 to 1992 produced by the Employment Projections division of the BLS.[24] Beginning with the standard "Make Table," we calculate each industry's share of commodity output and assume that it is the same regardless of whether the output is sold to final demand or to other industries as intermediate goods. Using each industry's share of commodity output, we allocate aggregate final demand by commodity across industry and then sum across commodities to estimate each industry's total production of final demand.

This procedure leads to a final demand share of 17% in 1977 and 22.2% in 1992 for the 13 non-manufacturing, computer-using industries. These shares are smaller than the GPO shares of 22% in 1977 and 28% in 1992 since several of the largest industries in this group, e.g., wholesale trade, sell relatively little to final demand. What we actually need, however, is the final demand share at the beginning of the period, but the Input-Output tables are not available that early on a consistent basis. To approximate this number, we calculate the average GPO share for 1958-73 and scale it by the ratios of the 1977 final demand to GPO share. This generates an estimate of a $s_1=13\%$ for the final demand share of the non-manufacturing, computer-using industries in the period 1958-73.

As discussed above, estimating the increased measurement error, $d(Du_1)$, is difficult, so we use several estimates from Table 9 to obtain a range. As such, these results should be viewed

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[23]See Ho, Jorgenson, and Stiroh (1999) for details.
[24]We use the BLS Input-Output tables rather than the official BEA Input-Output tables since the BLS provides a consistent set of accounts that have been adjusted to reflect SIC changes and are readily available from 1977 to 1992.

not as a precise estimate, but rather as a reasonable gauge to judge the economic importance of potential increased measurement error.

All estimates are based on the parameters from the difference-in-difference estimator, which makes the rather strong assumption that all relative changes in productivity, other than the amount attributed to total capital accumulation, is due to computers. This is a strong assumption since it does not account for the productivity impact from differences in changing labor quality, compositional changes in the capital stock, or technical change (TFP growth) that is independent of computer-use.

To estimate increased measurement error in non-manufacturing, computer-using industries due to computers, we compare the estimated computer impact in manufacturing to the estimated impact in non-manufacturing and interpret the difference as increased measurement error. The estimates in Table 9 suggest that the increase in measurement error in non-manufacturing, computer-using industries ranges from $d(Du_1)=0.74$ to 1.57 percentage points, after controlling for capital accumulation.

These two estimates are combined in the first panel of Table 11 to estimate the aggregate importance of the within effect. Multiplying the initial share of $s_1=13\%$ with an estimated increase in measurement error of $d(Du_1)=0.74\text{-}1.57\%$ suggests that the aggregate impact of the within effect is in the range of 0.10 to 0.20 percentage points. As pointed out by Baily and Gordon (1988), it is the relatively small final demand shares of these industries that prevent a larger aggregate impact.

(b) Between Effect

Estimating the between effect requires two similar pieces of information – the change in the final demand share and the original measurement error. Results are reported in the second panel of Table 11.

The change in the final demand shares is calculated from the data described above as $d(s_1)=0.22-0.13=0.09$. We do not, however, have an estimate of the original measurement error, Du_1, since our approach estimates the increase in measurement error associated with computers. To provide a comparable estimate to Sichel (1997), we assume the original measurement error in these industries was 1.66% per year, so that our lower estimate of increased measurement error yields a total of 2.4% that matches Sichel. These estimates imply the aggregate impact of the increased share of measurement error range from 0.22 to 0.30 percentage points. Although we are focusing on a different set of industries than Sichel (1997), it turns out that the change in shares was quite similar so this range includes his estimate of 0.23.

(c) Total Effect

The final panel in Table 11 combines the within and between effects to produce an estimate of the total impact of measurement error on aggregate productivity growth. The data suggest that measurement bias contributed 0.32 to 0.50 percentage points to the aggregate productivity slowdown. Approximately two-thirds of this is from the between effect as the non-manufacturing, computer-using industries account for a growing share of output and the other one-third is due to the within effect and increased measurement error within those industries.

(d) Is This Important?

The obvious question is whether these effects are large and important. According to BLS (1999-Table1), labor productivity growth for the private business sector fell from 3.2% for 1958-73 to 1.3% for 1990-96, a decline of 1.9%. Our estimates suggest that perhaps 0.4%, our midpoint, is due to increasing measurement problems, which is roughly one-fifth of the aggregate slowdown in the 1990s.

In contrast, Sichel (1997) concludes that his 0.23 measurement error contribution is "small compared to the overall 1.5 percentage points a year slowdown (pg. 370)." Griliches (1997), however, viewed those results as an important part of the explanation of the slowdown. We interpret our results as supporting the Griliches viewpoint that measurement error is important, contributing to both the aggregate productivity slowdown and the growing divergence in productivity growth between manufacturing and non-manufacturing industries. On the other hand, measurement error is obviously not the whole story.

It is also important to note also that our estimate is only from the 13 non-manufacturing industries that use computers intensively and thus is not comprehensive. For example, productivity growth has slowed steadily in construction, utilities, local and interurban passenger transit, and air transportation, but we make no attempt to quantify measurement problems in these industries.[25] Moreover, some of the industries that are often cited for measurement error related to computers such as retail trade and health services are not in the computer intensive

[25]Baily and Gordon (1988) provide a detailed analysis of measurement and data problems in construction and air transportation.

category even though they now rely heavily on computers. Thus, we conclude that measurement error has a played a meaningful role in the productivity slowdown, but it is clearly not the only explanation.

VIII. Conclusions

This paper explores the possibility that measurement problems contributed to the aggregate slowdown in U.S. productivity and growing productivity divergence across industries. Using productivity gains associated with increased computer intensity in manufacturing to identify potential increases in measurement error in non-manufacturing, we find evidence suggesting that measurement problems have worsened in non-manufacturing. More specifically, the empirical estimates suggest that productivity growth in 13 non-manufacturing industries that use computers intensely may be understated by between 0.7 and 1.6 percentage points per year over the period 1990-96.

This rather large measurement error appears to be associated with an inability to correctly measure and quantify the output from information technology. These problems lead to highly distorted productivity trends at the industry level, but have a more modest impact on aggregate productivity since the industries produce a small portion of final demand. The small shares of these industries in final demand mean that the aggregate impact of increased measurement error is only 0.10 to 0.20 percentage points per year.

Worsening measurement of output in the 1990s due to computers, however, is only part of the problem. The total understatement of aggregate output is obtained by adding errors arising from the increased share of the hard-to-measure non-manufacturing sector in GDP to the increased measurement error that we estimated. Building on the work of Sichel (1997), we put the increased share effect between 0.22 and 0.30 percentage points.

Thus, when one accounts for both sources of measurement error, growth in aggregate productivity may be understated by 0.32 to 0.50 percentage points per year for the 1990-96 period. While this represents a modest 20% of the overall productivity slowdown, it is not a trivial number and implies that measurement problems are playing an important role in U.S. productivity trends. For example, labor productivity growth would have been 1.7 percent instead of 1.3 percent in the 1990-96 period in the absence of this measurement error. During the period 1997-99 reported productivity growth increased substantially to about 2.3 percent per year.

While our empirical work is based on data through 1996, if we assume that the underestimate applies to the 1997-99 period, then true productivity growth may be closer to 2.7 percent.

Although it is difficult to put a precise number on the size of aggregate productivity growth error, it is clear that accurate measurement is important. Information about current and future productivity growth is a key issue for policy makers since labor productivity growth is a primary determinant of how fast an economy can grow. Productivity growth plus the growth in labor input places an upper limit on the sustainable growth rate for an economy. While many factors determine how fast labor will grow, e.g., immigration and social insurance policies, demographic projections suggest that about 1 percent a year is a reasonable estimate for labor growth. 2.7 percent growth in productivity then implies a sustainable output growth rate of about 3.7 if recent trends were to continue and potential measurement errors accounted for.

This is high by historical standards, but one must be careful about drawing conclusions. Changes in how output and productivity are measured do not change the true, underlying trends. Simply because official data may not be properly measuring the impact of new products, improved quality, or innovations does not imply consumers and firms are not enjoying the benefits. Moreover, as pointed out by Blinder (1997), there are no implications about resource constraints or spare productive capacity: "Official data may badly understate productivity growth. But if so, we are growing faster than the data say, and the policy needn't change (pg. 60)." Nonetheless, correctly measuring productivity has important implications for business and the economy through contractual inflation adjustments and the tax code, as well as for gauging relative performance. Only by correctly measuring output can we understand the impact of the information technology revolution.

These calculations are illustrative, but there are a number of reasons not to take them too literally. Ongoing statistical programs are continuously improving the way the data is collected and processed. For example, there have been a number of recent changes in the deflators used to translate revenue into real output in many industries. Moreover, the BEA benchmark revision in 1999 revised many of its procedures to better measure output, e.g., real output growth in banking is no longer based on changes in input use. On the other side, however, our estimates are only for the 13 most computer-intensive industries. Inclusion of industries such as health, construction, and airlines, all of which make substantial use of computers and have serious measurement problems, could add to our estimates.

The obvious area for future research is work from the bottom up to examine product trends in these industries, perhaps from the firm level. By generating alternative output and productivity series from micro data, it would be possible to gauge the accuracy of the official industry productivity series and the reasonableness of our imputations. While BLS and BEA have made important progress in these areas, this remains an exciting area for future productivity research.

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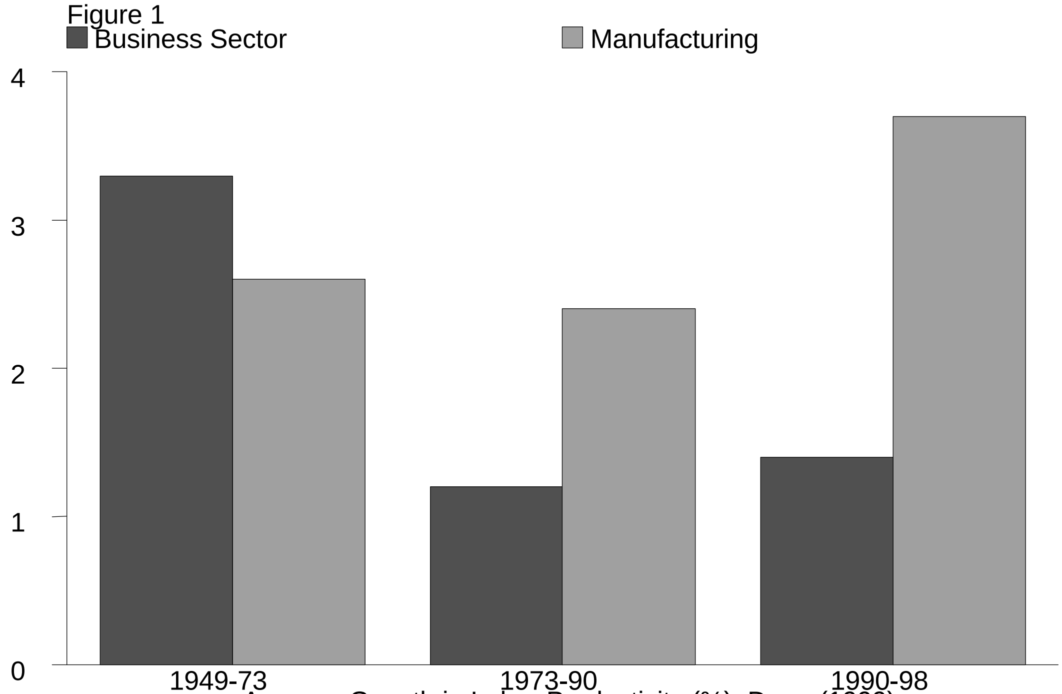
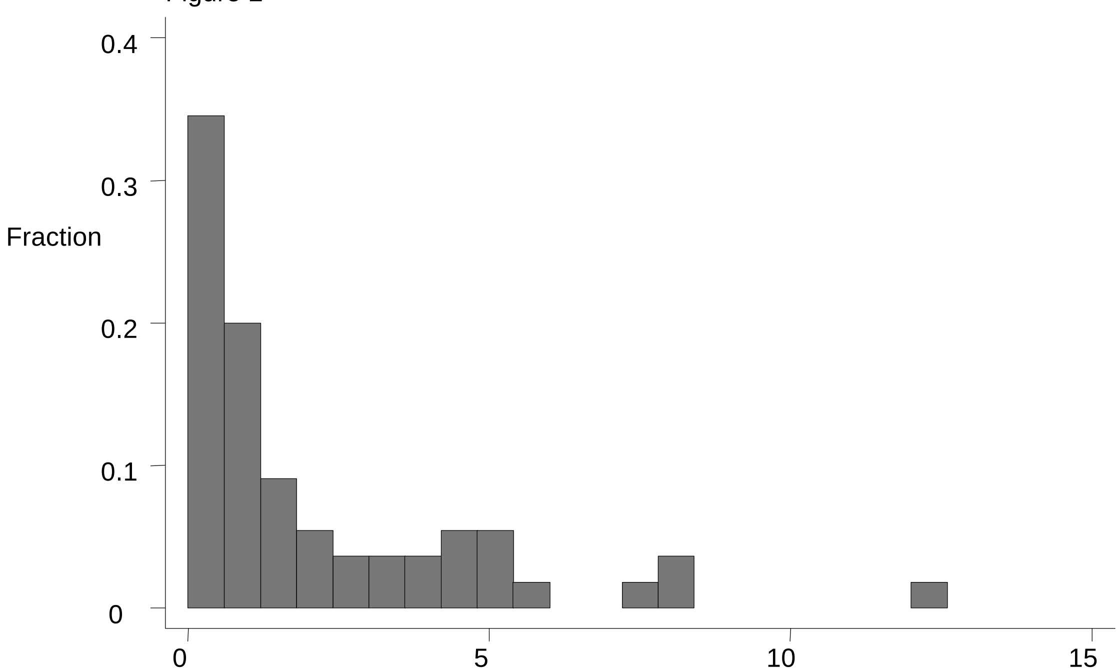
Figure 1



Average Growth in Labor Productivity (%), Dean (1999)

Figure 2



Distribution of Nominal Computer Capital Shares, 1990

Table 1: Change in Computer Intensity by Major Sector and Detailed Industries, 1970-1996

Industry	Nominal Computer Capital Share			Real Computer Capital Growth Rates				Growth in Total Capital
	1980	1990	1996	1970-80	1980-90	1990-96	1970-96	1970-96
AGRICULTURE, FORESTRY & FISHING	0.011	0.020	0.016	22.77	20.11	15.36	19.93	0.96
Farms	0.002	0.004	0.002	0.00	20.26	8.13	15.71	0.59
Agricultural services, forestry and fishing	0.131	0.156	0.099	21.70	20.15	16.50	19.83	4.65
MINING	0.169	0.233	0.140	36.62	18.83	8.34	23.25	1.77
Metal mining	0.039	0.041	0.020	22.54	18.14	8.46	16.70	1.50
Coal mining	0.004	0.016	0.030	0.00	14.48	29.37	17.83	2.98
Oil and gas extraction	0.203	0.274	0.158	36.99	18.72	7.16	23.08	1.67
Nonmetallic minerals, except fuels	0.008	0.122	0.241	0.00	30.34	26.41	28.86	1.47
CONSTRUCTION	0.147	0.238	0.113	16.67	19.52	7.77	15.71	0.90
MANUFACTURING	0.926	1.758	1.747	27.61	23.58	19.77	24.25	2.27
DURABLE MANUFACTURING	1.346	2.291	2.097	28.94	22.40	18.17	23.94	2.21
Lumber and wood products	0.869	0.494	0.899	26.83	10.01	27.94	20.62	1.44
Furniture and fixtures	0.966	1.893	1.570	29.95	24.98	16.59	24.54	2.54
Stone, clay, and glass products	1.688	2.353	1.354	37.05	19.78	9.79	24.12	0.77
Primary metal industries	0.283	0.474	0.492	21.18	19.78	18.49	20.02	-0.15
Fabricated metal products	0.464	0.986	1.037	23.54	24.50	20.28	23.16	2.15
Industrial machinery and equipment	3.664	4.557	3.255	27.92	20.49	14.06	21.86	3.50
Electronic and other electric equipment	2.130	3.200	3.585	40.23	23.68	23.88	30.09	4.96
Transportation equipment	0.862	1.962	1.801	28.49	25.04	17.90	24.72	2.11
Instruments and related products	1.324	3.742	3.348	27.39	30.47	18.03	26.41	4.69
Miscellaneous manufacturing industries	0.685	1.519	2.034	15.15	23.79	24.43	20.61	1.95
NON-DURABLE MANUFACTURING	0.452	1.170	1.382	24.08	26.76	22.74	24.80	2.35
Food and Kindred Products	0.360	0.842	1.069	25.21	25.20	23.99	24.93	1.86
Tobacco products	0.527	1.128	1.318	12.70	24.80	19.14	19.35	3.68
Textile mill products	0.262	0.517	0.640	13.54	21.98	21.61	18.65	0.15
Apparel and other textile products	1.191	0.864	1.914	17.40	11.85	31.10	18.43	2.09
Paper and allied products	0.392	0.982	0.685	25.76	28.05	13.70	23.86	2.61
Printing and publishing	1.388	4.469	3.943	29.11	31.89	17.12	27.41	3.39
Chemicals and allied products	0.289	0.854	1.531	25.78	26.82	29.78	27.10	2.93
Petroleum and coal products	0.385	0.659	0.857	25.54	22.66	24.72	24.24	1.76
Rubber and miscellaneous plastics products	0.664	1.120	1.376	21.85	23.84	25.75	23.52	3.38
Leather and leather products	0.851	1.344	1.482	10.88	17.30	19.06	15.24	-0.64
TRANSPORTATION, COMM., & UTILITIES	0.106	0.332	0.300	24.59	27.77	18.55	24.42	2.07
Railroad transportation	0.013	0.023	0.009	17.37	20.26	4.92	15.61	-0.83
Local and interurban passenger transit	0.112	0.170	0.030	9.51	18.44	-10.77	8.27	-1.24
Trucking and warehousing	0.047	0.060	0.051	9.97	19.90	20.18	16.15	3.20
Water transportation	0.057	0.098	0.100	5.84	18.15	18.44	13.48	0.26
Transportation by air	0.438	0.869	0.404	25.16	26.31	10.36	22.19	3.24
Pipelines, except natural gas	0.050	0.026	0.198	11.16	2.13	51.93	17.09	1.09
Transportation services	0.163	1.261	0.316	13.49	36.78	2.88	20.00	2.24
Communications	0.153	0.441	0.575	29.79	28.12	24.73	27.98	4.54
Utilities	0.112	0.359	0.283	28.52	28.54	15.96	25.63	2.40
WHOLESALE TRADE	3.113	4.636	6.948	34.17	25.01	28.84	29.42	6.38
RETAIL TRADE	0.592	1.705	1.853	31.57	29.08	23.48	28.75	3.61
FINANCE, INSURANCE & REAL ESTATE	1.322	2.277	2.285	32.10	27.07	21.33	27.68	4.39
Depository institutions	4.439	5.314	3.273	35.51	24.94	14.01	26.48	7.40
Non-depository; holding and investment offices	3.576	5.626	6.981	29.13	28.43	26.67	28.29	7.48
Security and commodity brokers	9.442	7.411	8.712	28.97	20.70	21.00	23.95	6.77
Insurance carriers	6.381	7.979	5.170	31.18	32.49	19.42	28.97	11.17
Insurance agents, brokers and services	8.572	5.062	4.295	29.11	10.41	16.10	18.91	3.24
Real estate	0.164	0.452	0.928	26.50	29.89	31.00	28.84	3.09
SERVICES	1.582	4.083	4.966	28.44	28.29	25.22	27.64	4.41
Hotels and other lodging places	0.236	0.338	0.167	29.10	23.07	8.98	22.14	2.74
Personal services	0.619	2.979	1.099	37.52	32.84	6.03	27.70	1.77
Business Services	4.408	12.458	20.406	36.25	27.63	29.46	31.37	5.34
Auto repair, services, and garages	0.970	3.870	0.907	35.51	34.09	3.18	27.50	5.22
Miscellaneous repair shops	0.986	2.660	2.454	29.54	27.42	20.22	26.33	3.16
Motion pictures	1.554	3.069	1.868	47.04	28.99	19.37	31.97	6.06
Amusement and recreation services	0.481	0.841	0.856	35.62	21.08	23.56	26.15	2.37
Health services	0.600	1.423	1.924	24.75	30.94	27.38	27.74	5.67
Legal services	2.199	7.869	5.852	19.08	35.82	12.89	24.09	4.74
Educational services	2.450	1.166	0.685	18.50	13.05	15.80	15.78	8.22
Other	2.446	4.936	5.849	20.92	25.46	23.96	23.37	4.97
PRIVATE BUSINESS SECTOR	0.678	1.575	1.847	29.97	26.17	22.96	26.89	2.90

Notes: Shares and growth rates are percentages.
Source: BEA (1998) and authors' calculations.

Table 2: Distribution of Capital within Major Sectors and Detailed Industries, 1996

Industry	Nominal Capital Stock Share					Total Value of Capital Stock
	Computer	Other Hi-Tech	Total Hi-Tech	Lo-Tech	Structures	
AGRICULTURE, FORESTRY & FISHING	0.02	0.87	0.89	41.76	57.38	366,430
Farms	0.00	0.04	0.04	38.22	61.69	315,425
Agricultural services, forestry and fishing	0.10	5.95	6.05	63.35	30.53	51,276
MINING	0.14	1.89	2.03	16.88	81.05	436,641
Metal mining	0.02	0.99	1.01	19.78	79.20	35,165
Coal mining	0.03	0.42	0.45	33.89	65.67	36,171
Oil and gas extraction	0.16	2.17	2.33	13.22	84.45	344,343
Nonmetallic minerals, except fuels	0.24	1.34	1.58	43.03	55.42	20,745
CONSTRUCTION	0.11	0.81	0.92	59.31	39.80	88,188
MANUFACTURING	1.75	6.30	8.05	51.47	40.49	1,480,426
DURABLE MANUFACTURING	2.10	5.98	8.08	51.71	40.23	759,300
Lumber and wood products	0.90	2.05	2.95	47.03	50.05	29,331
Furniture and fixtures	1.57	1.81	3.38	36.76	59.87	13,316
Stone, clay, and glass products	1.35	4.94	6.29	51.33	42.41	43,403
Primary metal industries	0.49	2.76	3.25	58.89	37.80	127,819
Fabricated metal products	1.04	2.23	3.27	62.95	33.76	81,906
Industrial machinery and equipment	3.26	6.61	9.87	51.76	38.33	128,598
Electronic and other electric equipment	3.59	12.87	16.46	45.54	38.01	128,802
Transportation equipment	1.80	3.23	5.03	54.43	40.55	139,315
Instruments and related products	3.35	13.23	16.58	33.44	49.98	53,024
Miscellaneous manufacturing industries	2.03	3.28	5.31	43.11	51.59	14,001
NON-DURABLE MANUFACTURING	1.38	6.64	8.02	51.19	40.77	721,018
Food and Kindred Products	1.07	4.64	5.71	49.47	44.86	145,868
Tobacco products	1.32	3.47	4.79	46.96	48.27	9,182
Textile mill products	0.64	2.95	3.59	52.71	43.74	37,655
Apparel and other textile products	1.91	2.81	4.72	39.85	55.41	13,332
Paper and allied products	0.68	4.69	5.37	69.13	25.47	98,503
Printing and publishing	3.94	9.66	13.60	42.69	43.72	60,044
Chemicals and allied products	1.53	11.13	12.66	48.87	38.47	206,387
Petroleum and coal products	0.86	5.16	6.02	41.35	52.64	92,578
Rubber and miscellaneous plastics products	1.38	2.07	3.45	61.77	34.81	54,711
Leather and leather products	1.48	0.84	2.32	31.12	66.51	2,629
TRANSPORTATION, COMM., & UTILITIES	0.30	12.42	12.72	23.81	63.51	2,301,741
Railroad transportation	0.01	1.77	1.78	11.93	86.24	360,656
Local and interurban passenger transit	0.03	6.56	6.59	21.39	72.00	19,912
Trucking and warehousing	0.05	3.61	3.66	72.73	23.59	108,208
Water transportation	0.10	4.04	4.14	76.74	19.10	36,002
Transportation by air	0.40	7.94	8.34	72.31	19.36	110,141
Pipelines, except natural gas	0.20	1.71	1.91	8.68	89.38	48,361
Transportation services	0.32	12.16	12.48	71.34	16.20	42,660
Communications	0.58	36.83	37.41	7.44	55.17	562,226
Utilities	0.28	5.04	5.32	23.51	71.15	1,014,044
WHOLESALE TRADE	6.95	10.34	17.29	33.21	49.47	402,858
RETAIL TRADE	1.85	1.85	3.70	22.68	73.67	540,565
FINANCE, INSURANCE & REAL ESTATE	2.28	5.11	7.39	16.95	75.62	1,960,245
Depository institutions	3.27	8.14	11.41	30.79	57.81	370,374
Non-depository; holding and investment offices	6.98	11.52	18.50	55.51	26.02	151,641
Security and commodity brokers	8.71	5.62	14.33	13.89	71.78	11,542
Insurance carriers	5.17	8.79	13.96	27.36	58.67	180,296
Insurance agents, brokers and services	4.29	6.79	11.08	29.91	59.01	6,449
Real estate	0.93	2.87	3.80	6.55	89.64	1,239,803
SERVICES	4.97	8.83	13.80	30.19	56.06	754,670
Hotels and other lodging places	0.17	1.28	1.45	9.20	89.37	127,093
Personal services	1.10	6.31	7.41	28.96	63.63	26,266
Business Services	20.41	14.20	34.61	37.01	28.34	126,464
Auto repair, services, and garages	0.91	2.87	3.78	83.21	13.01	114,535
Miscellaneous repair shops	2.45	2.13	4.58	59.37	36.00	11,987
Motion pictures	1.87	23.21	25.08	22.24	52.73	29,366
Amusement and recreation services	0.86	1.29	2.15	25.84	71.96	48,536
Health services	1.92	14.30	16.22	12.64	71.16	153,883
Legal services	5.85	11.48	17.33	26.79	55.87	18,922
Educational services	0.69	1.46	2.15	6.93	91.00	18,221
Other	5.85	12.56	18.41	18.01	63.60	79,647
PRIVATE BUSINESS SECTOR	1.85	7.32	9.17	28.87	61.99	8,328,842

Notes: Shares are percentages and values are millions of current dollars.

Source: BEA (1998) and authors' calculations.

Table 3: Distribution of High-Tech Capital Across Major Sectors, 1996

Industry	Computer Capital		High-Tech Capital	
	Nominal Value	Percent of Total	Nominal Value	Percent of Total
AGRICULTURE, FORESTRY & FISHING	58	0.04	3,243	0.42
MINING	612	0.40	8,874	1.16
CONSTRUCTION	100	0.06	811	0.11
DURABLE MANUFACTURING	15,919	10.35	61,278	8.02
NON-DURABLE MANUFACTURING	9,965	6.48	57,829	7.57
TRANSPORTATION, COMM., & UTILITIES	6,905	4.49	292,832	38.35
WHOLESALE TRADE	27,991	18.20	69,677	9.12
RETAIL TRADE	10,018	6.51	20,009	2.62
FINANCE, INSURANCE & REAL ESTATE	44,789	29.11	144,988	18.99
SERVICES	37,475	24.36	104,160	13.64
PRIVATE BUSINESS SECTOR	153,833	100.00	763,700	100.01

Notes: Shares are percentages and values are millions of current dollars.
Source: BEA (1998) and authors' calculations.

Table 4: 10 Largest Owners of Computer and High-Tech Capital, 1996

Industry	Value of Capital Stock	Share of Total
	Computer Capital	
Wholesale Trade	27,991	18.20
Business Services	25,806	16.78
Depository Institutions	12,123	7.88
Real Estate	11,505	7.48
Non-depository; holding and investment offices	10,587	6.88
Retail Trade	10,018	6.51
Insurance Carriers	9,321	6.06
Other Services	4,658	3.03
Electronic and other electric equipment	4,618	3.00
Industrial Machinery and Equipment	4,186	2.72
Sum of Top 10	120,814	78.53
Total	153,833	100.00
	High-Tech Capital	
Communications	210,299	27.54
Wholesale Trade	69,677	9.12
Utilities	53,943	7.06
Real Estate	47,049	6.16
Business Services	43,748	5.73
Depository Institutions	42,277	5.54
Non-depository; holding and investment offices	28,072	3.68
Chemicals and allied products	26,138	3.42
Insurance Carriers	25,162	3.29
Health services	24,956	3.27
Sum of Top 10	571,321	74.82
Total	763,700	100.00

Notes: Shares are percentages and values are millions of current dollars.
Source: BEA (1998) and authors' calculations.

Table 5: Growth in Labor Productivity by Major Sector and Detailed Industries, 1958-1996

Industry	1958-73	1973-79	1979-90	1990-96	1996 Gross Output
AGRICULTURE, FORESTRY & FISHING	4.52	2.29	2.22	0.51	289.3
Farms	5.17	3.52	4.07	1.99	247.1
Agricultural services, forestry and fishing	-1.59	-1.88	1.13	-1.28	42.3
MINING	4.05	-6.04	1.40	2.39	135.9
Metal mining	2.56	-6.71	3.35	4.25	11.0
Coal mining	4.66	-2.99	7.53	6.32	22.1
Oil and gas extraction	4.12	-9.01	-0.58	1.54	85.7
Nonmetallic minerals, except fuels	3.92	-0.95	0.79	2.00	17.2
CONSTRUCTION	0.47	-0.99	-0.98	-0.49	696.9
MANUFACTURING	2.73	1.06	1.85	3.54	3,731.4
DURABLE MANUFACTURING	2.77	0.18	2.18	4.76	2,002.2
Lumber and wood products	2.72	0.31	1.56	-0.51	106.8
Furniture and fixtures	2.34	1.20	1.31	2.36	54.7
Stone, clay, and glass products	2.34	0.13	1.27	2.11	79.8
Primary metal industries	3.21	-1.25	1.61	4.16	182.5
Fabricated metal products	2.08	0.07	1.19	2.84	209.5
Industrial machinery and equipment	2.30	-0.24	4.66	8.35	372.2
Electronic and other electric equipment	3.25	2.20	4.10	8.74	321.5
Transportation equipment	3.20	0.27	0.80	4.17	478.5
Instruments and related products	3.70	3.28	2.98	4.22	145.6
Miscellaneous manufacturing industries	3.68	-0.54	1.44	1.99	50.0
NON-DURABLE MANUFACTURING	2.80	2.14	1.39	2.17	1,729.1
Food and Kindred Products	2.62	1.88	1.89	1.53	455.2
Tobacco products	2.63	0.96	1.56	3.39	41.3
Textile mill products	3.17	3.55	2.61	3.46	77.2
Apparel and other textile products	2.08	1.61	1.91	4.35	80.5
Paper and allied products	3.10	1.62	1.76	1.79	161.5
Printing and publishing	1.85	-0.11	0.21	0.38	197.2
Chemicals and allied products	4.60	1.41	1.16	2.61	373.3
Petroleum and coal products	4.38	3.62	2.61	3.04	185.7
Rubber and miscellaneous plastics products	3.36	-0.67	1.94	3.18	149.6
Leather and leather products	0.65	-0.11	1.68	1.25	8.1
TRANSPORTATION, COMM., & UTILITIES	4.13	2.60	0.34	0.89	1,064.1
Railroad transportation	5.87	1.92	3.30	4.54	38.1
Local and interurban passenger transit	1.02	0.17	-0.95	-7.91	11.5
Trucking and warehousing	2.17	1.00	0.23	3.89	215.9
Water transportation	4.58	1.90	1.75	0.36	38.9
Transportation by air	4.38	3.43	1.15	-2.57	136.3
Pipelines, except natural gas	8.82	-0.87	0.40	8.01	11.5
Transportation services	1.31	1.50	0.69	-1.85	39.4
Communications	3.91	6.68	2.55	3.81	329.9
Utilities	4.26	0.59	-1.75	-0.28	242.1
WHOLESALE TRADE	3.27	0.88	2.50	4.90	804.4
RETAIL TRADE	1.95	-0.67	0.37	1.18	1,037.5
FINANCE, INSURANCE & REAL ESTATE	1.06	0.74	0.31	0.60	1,404.4
Depository institutions	0.97	1.44	-0.78	0.39	362.2
Non-depository; holding and investment offices	-0.24	16.87	3.96	-0.45	33.0
Security and commodity brokers	-7.50	1.96	4.09	7.56	108.1
Insurance carriers	2.02	2.16	0.52	0.68	265.8
Insurance agents, brokers and services	0.47	1.69	-1.40	-6.54	64.5
Real estate	1.89	-1.00	0.14	0.81	571.3
SERVICES	0.65	-0.57	-0.35	-0.65	2,497.3
Hotels and other lodging places	0.23	1.16	-2.58	2.78	109.5
Personal services	2.12	-1.30	-1.94	-1.16	74.8
Business services	-0.29	-1.18	-1.51	0.10	469.8
Auto repair, services, and garages	1.40	-3.60	0.18	3.33	221.4
Miscellaneous repair shops	0.08	1.51	-0.97	-2.86	42.0
Motion pictures	-2.27	3.39	2.03	-0.40	69.4
Amusement and recreation services	-0.03	1.67	0.64	-1.31	105.4
Health services	0.82	-1.25	-0.06	-1.16	675.8
Legal services	0.69	-2.05	-2.46	-2.98	114.3
Educational services	0.27	-1.03	0.17	-1.21	95.9
Other	0.49	-0.43	0.04	-1.41	518.5
PRIVATE BUSINESS SECTOR	2.29	0.13	0.25	1.02	11,661.2
ECONOMY	2.12	0.36	0.34	1.10	13,370.5

Notes: Growth rates are percentages and values are billions of current dollars.

Source: BLS Gross Output by Industry and BEA Employment by Industry.

Table 6: Classification of Industries

Manufacturing Industries	Non-Manufacturing Industries
Computer-Using Industries	
Stone, clay, and glass products	Wholesale Trade
Industrial machinery and equipment	Depository institutions
Electronic and other electric equipment	Non-depository; holding and investment offices
Instruments and related products	Security and commodity brokers
Printing and publishing	Insurance carriers
	Insurance agents, brokers and services
	Personal services
	Business services
	Auto repair, services, and garages
	Miscellaneous repair shops
	Motion pictures
	Legal services
	Other services
Non-Computer-Using Industries	
Lumber and wood products	Farms
Furniture and fixtures	Agricultural services, forestry and fishing
Primary metal industries	Metal mining
Fabricated metal products	Coal mining
Transportation equipment	Oil and gas extraction
Miscellaneous manufacturing industries	Nonmetallic minerals, except fuels
Food and Kindred Products	Construction
Tobacco products	Railroad transportation
Textile mill products	Local and interurban passenger transit
Apparel and other textile products	Trucking and warehousing
Paper and allied products	Water transportation
Chemicals and allied products	Transportation by air
Petroleum and coal products	Pipelines, except natural gas
Rubber and miscellaneous plastics products	Transportation services
Leather and leather products	Communications
	Utilities
	Retail Trade
	Real estate
	Hotels and other lodging places
	Health services
	Amusement and recreation services
	Educational services

Notes: Computer-using industries are defined as the top one-third industries in terms of 1990 nominal stock of computer capital as a share of total capital stock.

Table 7: Average Growth in Labor Productivity

	Number of Inudstries	1958-73	1973-79	1979-90	1990-96	1990-96 less 1958-73	1990-96 less 1979-90
				Weighted Average			
All Industries	54	2.066	0.305	0.687	1.042	-1.024	0.355
Manufacturing Industries	20	2.824	0.831	2.303	3.751	0.927	1.448
Computer-Using	5	2.659	0.900	3.165	5.575	2.916	2.410
Non-Computer-Using	15	2.901	0.796	1.815	2.722	-0.179	0.907
Non-Manufacturing Industries	35	1.750	0.115	0.284	0.461	-1.289	0.177
Computer-Using	13	1.341	0.661	0.257	0.583	-0.758	0.326
Non-Computer-Using	22	1.944	-0.161	0.300	0.383	-1.561	0.083
				Unweighted Average			
All Industries	54	2.168	0.668	1.344	1.600	-0.568	0.256
Manufacturing Industries	20	2.864	0.960	2.164	3.170	0.306	1.006
Computer-Using	5	2.689	1.051	2.827	4.762	2.073	1.935
Non-Computer-Using	15	2.923	0.929	1.943	2.640	-0.283	0.697
Non-Manufacturing Industries	35	1.770	0.501	0.876	0.703	-1.067	-0.173
Computer-Using	13	0.093	1.643	0.497	0.089	-0.004	-0.408
Non-Computer-Using	22	2.762	-0.174	1.099	1.065	-1.697	-0.034

Notes: Growth rates are percentages.

Source: BLS Gross Output by Industry and BEA Employment by Industry.

Table 8: Tests of the Equality of Mean Productivity Acceleration

	No. of Obs.	1990-96 less 1958-73	1990-96 less 1979-90
Mfg vs. Non-Mfg	20 vs. 35	1.373	1.179
		(.949)	(.708)
		p=0.15	p=0.10
Computer-Using vs. Non-Computer-Using	18 vs. 37	1.697	-0.019
		(.964)	(.745)
		p=0.08	p=0.98
Non-Mfg, Computer-Using vs. Non-Mfg, Non-Computer-Using	13 vs. 22	1.693	-0.373
		(1.342)	(1.03)
		p=0.21	p=0.72
Mfg, Computer-Using vs. Mfg, Non-Computer-Using	5 vs. 15	2.355	1.237
		(1.068)	(.803)
		p=0.04	p=0.14

Notes: Value is the mean, unweighed difference in productivity acceleration. Standard errors of the differences are in parenetheses. p is the p-value associated with the null hypothesis that the mean acceleration is equal between the groups.

Table 9: Estimated of Acceleration of Labor Productivity Growth for Manufacturing and Non-Manufacturing
Dependent Variable: Δy

	OLS				**Weighted OLS**			
	Non-Mfg	Mfg	Non-Mfg	Mfg	Non-Mfg	Mfg	Non-Mfg	Mfg
T	-1.697	-0.283	-0.648	-0.033	-1.561	-0.179	-0.663	0.068
	(0.944)	(0.552)	(0.845)	(0.566)	(0.596)	(0.638)	(0.502)	(0.649)
C	-2.668	-0.233	-3.070	-0.312	-0.603	-0.242	-1.542	-0.306
	(.827)	(0.589)	(0.721)	(0.581)	(.662)	(0.578)	(0.554)	(0.571)
T*C	1.693	2.355	1.576	2.320	0.803	3.096	1.434	2.997
	(1.549)	(1.103)	(1.339)	(1.084)	(.996)	(1.081)	(.807)	(1.067)
Δ(K/L)			0.657	0.251			0.640	0.276
			(0.136)	(0.164)			(0.105)	(0.187)
Constant	2.762	2.922	0.962	2.240	1.944	2.901	0.227	2.184
	(0.504)	(0.295)	(0.574)	(0.532)	(0.375)	(0.325)	(0.413)	(0.581)
No. of Obs.	70	40	70	40	70	40	70	40
Adjusted R^2	0.28	0.83	0.46	0.83	0.30	0.83	0.55	0.83

Notes: T=1 if 1990-96; T=0 if 1958-73. C=1 if computer-using; C=0 if non-computer-using. Weighted OLS uses industry employment estimates as the weights. Standard errors are in parentheses and are corrected for heteroskedasticity from different length periods by weighted each observation by the squared root of the length of the period.

Table 10: Annual Production Function Estimates, 1979-96

	Dependent Variable: lnY			Dependent Variable: ln(Y/L)		
	OLS^	FE*	BE	OLS^	FE*	BE
ln(K2)	0.104	-0.003	0.109			
	(0.01)	(0.013)	(0.042)			
M*ln(K2)	0.068	0.016	0.069			
	(.005)	(0.008)	(0.022)			
ln(K1)	0.288	0.147	0.289			
	(0.013)	(0.032)	(0.053)			
lnL	0.523	0.469	0.519			
	(0.015)	(0.028)	(0.061)			
K2/K				0.698	-0.944	2.467
				(0.639)	(0.234)	(3.668)
K2/K*M				13.873	4.462	20.732
				(1.689)	(0.661)	(8.966)
ln(K/L)				0.366	0.340	0.383
				(0.013)	(0.026)	(0.055)
Constant	4.227	6.534	4.073	3.079	3.217	2.992
	(0.148)	(0.309)	(0.549)	(0.077)	(0.107)	(0.271)
No. of Obs.	935	935	935	935	935	935
R^2	0.85	0.67	0.86	0.50	0.49	0.53

Notes: M=1 if manufacturing; M=0 if non-manufacturing. ^ signifies year dummy variables are not ^{2} ^{2} for ^{2} for fixed effects, and between-R for between estimator. Standard errors are in

Table 11: The Aggregate Impact of Mismeasurement in the Computer-Using, Non-Manufacturing Industries

Actual ALP Growth 1990-96 (3a)	Increased Measurement Error (4a)	Imputed ALP Growth 1990-96 (5a)=(3a)+(4a)	Final Demand Share 1958-73 (6a)	Within Effect (7a)=(4a)*(6a)	Share of Aggregate Slowdown of 1.9% (9a)
0.09	1.57	1.66	0.130	0.204	10.7%
0.09	0.74	0.83	0.130	0.096	5.1%

Measurement Error: Original (1b)	Measurement Error: Increase (2b)	Measurement Error: Total (3b)=(1b)+(2b)	Final Demand Share: 1958-73 (4b)	Final Demand Share: 1992 (5b)	Final Demand Share: Change in (6b)=(5b)-(4b)	Between Effect (7b)=(3b)*(6b)	1.9% (9b)
1.66	1.57	3.23	0.130	0.222	0.092	0.297	15.6%
1.66	0.74	2.40	0.130	0.222	0.092	0.221	11.6%

Total Effect (7c)=(7a)+(7b)	1.9% (9c)
0.501	26.4%
0.317	16.7%