Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say? — Source link

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Information Technology and the U.S. Productivity Revival:
What Do the Industry Data Say?

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Abstract

This paper examines the link between information technology (IT) and the U.S. productivity revival in the late 1990s. Industry-level data show a broad productivity resurgence that reflects both the production and the use of IT. The most IT-intensive industries experienced significantly larger productivity gains than other industries and a wide variety of econometric tests show a strong correlation between IT capital accumulation and labor productivity. To quantify the aggregate impact of IT-use and IT-production, a novel decomposition of aggregate labor productivity is presented. Results show that virtually all of the aggregate productivity acceleration can be traced to the industries that either produce IT or use IT most intensively, with essentially no contribution from the remaining industries that are less involved in the IT revolution.

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I. Introduction

Two of the defining characteristics of the U.S. economy in recent years have been accelerating productivity growth and strong investment in computers and other information technology (IT) assets.[1] Why? Is there a link? A consensus is now emerging that both the *production* and the *use* of IT have contributed substantially to the aggregate productivity revival in the late 1990s (Bureau of Labor Statistics (2000a, 2000b), Council of Economic Advisors (2001), Jorgenson and Stiroh (2000), Oliner and Sichel (2000), and Whelan (2000a)).[2] These aggregate results add to a large body of earlier microeconomic studies that typically found a large economic impact from IT-use (see surveys by Brynjolfsson and Yang (1996) and Brynjolfsson and Hitt (2000a)).

Not everyone is convinced, however. Most notably, Gordon (1999, 2000) argues that the majority of the recent productivity acceleration is due to cyclical forces with the remainder concentrated in the relatively small portion of the economy engaged in the *production* of IT and other durable goods. Kiley (1999, 2000) argues that large adjustment costs blunt the impact of IT investment and may have actually *reduced* productivity growth in periods of rapid IT investment. Roach (1998) argues much of the productivity revival is a statistical mirage due to the *understatement* of actual hours worked, which leads productivity growth to be *overstated*, as the white-collar workweek expands faster than the data measure.

The goal of this paper is to shed some light on the issue by moving beneath the aggregate data to examine the productivity performance in the late 1990s of the individual industries that either produce IT, use IT, or are relatively isolated from the IT revolution. By examining variation in productivity growth over time and across industries and by exploring the link with IT capital accumulation, one can better understand the role of IT in the U.S. productivity revival.

This type of disaggregated analysis has several clear advantages over the aggregate studies mentioned above. First, it quantifies the impact of IT from the bottom up, rather than a top-down decomposition that begins with aggregate data. This fully exploits the breadth and variation in the industry-level data, and avoids unnecessary or even misleading aggregation. Second, this approach tests econometrically for an economic impact from IT. In contrast, growth accounting techniques essentially assume the result when factor shares proxy for output elasticities. While growth

[1]This paper focuses on labor productivity, defined as real output per hour. Unless explicitly stated otherwise, productivity refers to labor productivity. When total factor productivity, defined as real output per total input used, is examined the full name is used.

[2]In addition, many "new economy" proponents have argued that it is the combination of information technology, globalization, and deregulation that is driving the U.S. economy.

accounting provides a valuable and well-tested means for understanding the proximate sources of growth, alternative methods are needed to corroborate those results.

This paper addresses two specific empirical questions regarding recent productivity gains and IT. First, is the U.S. productivity revival widespread, or is it concentrated in relatively few industries? This is important since it directly affects the strength and stability of the economy and has implications for the distribution of income and wealth. Second, are industry productivity gains linked to IT-use? By exploring the link between productivity gains and IT, this helps to quantify the returns to the massive IT investment and to resolve the debate about the growth impact of IT-use. The answer to both questions appears to be yes.

Industry-level data show that the recent U.S. acceleration in productivity is a broad-based phenomenon that reflects gains in a majority of industries through the late 1990s. For example, the mean productivity acceleration for 61 industries from 1987-95 to 1995-99 is 1.09 percentage points and the median is 0.67 percentage point. Nearly two-thirds of these industries show a productivity acceleration. Even when the particularly strong productivity industries that produce IT (or even durable goods manufacturing as a whole) are excluded, the data show a significant acceleration in productivity for the remaining industries. This suggests the U.S. productivity revival is not narrowly based in only a few IT-producing industries.

In terms of IT-use, a variety of complementary econometric specifications and tests show a strong link between IT investment and productivity gains. The productivity acceleration in the late 1990s for IT-intensive industries, for example, is about 1 percentage point larger than for other industries. Moreover, rapid IT capital deepening in the early 1990s is associated with faster productivity growth in the late 1990s, even after controlling for other input accumulation and productivity growth in the early 1990s. Production function estimates also show a significant and relatively large output elasticity for IT capital. Thus, a battery of econometric tests supports the conclusion that IT-use has been an important part of the U.S. productivity revival in the late 1990s.

These results raise doubts about the hypothesis that the recent productivity revival is due largely to gains in IT-producing industries and cyclical forces (Gordon, 1999, 2000). If gains were primarily due to IT-production, the productivity revival would not appear broad-based. If cyclical forces were driving the productivity gains, one might expect these gains to be equal across industries or at least to be independent of IT-intensity. In contrast, these results show that the most intensive users of IT experienced the largest productivity gains, consistent with the idea that IT has real economic benefits.

Finally, the paper presents a novel, although relatively straightforward, decomposition of aggregate labor productivity growth into the contribution of component industries, an approach that is similar to the total factor productivity decomposition of Domar (1961). This decomposition quantifies the direct contribution to aggregate productivity growth from three distinct groups of industries – those that produce IT, those that use IT most intensively, and the remaining industries that are relatively isolated from the IT revolution.

The data show a contribution to aggregate productivity in the 1990s from all three groups, although the vast majority comes from IT-related industries. For example, the 26 IT-using industries contributed 0.66 percentage point to the aggregate productivity acceleration and the two IT-producing industries 0.16. The 33 remaining industries contributed only 0.08. Once one accounts for reallocation of intermediate materials, the industries that either produce or use IT account for *all* of the aggregate productivity acceleration, with the other industries making a *negative* contribution to the acceleration of aggregate productivity growth in the late 1990s.

Both the econometric work and the decomposition provide strong evidence that IT-use has real economic benefits. The econometric work shows a significant relationship between IT capital deepening and productivity gains, while the decomposition shows these effects to be meaningful at the aggregate level. Taken together, the evidence points to a substantial role for IT in the recent U.S. productivity revival.

II. Framing the Debate on IT and Productivity

This section outlines the debate by reviewing the recent U.S. experience in terms of productivity growth and IT capital accumulation. The emerging consensus that IT is driving the productivity revival is summarized, and several alternative explanations for the U.S. productivity revival are discussed.

a. IT and the Productivity Revival

The U.S. productivity revival is by now familiar to most economists. After more than two decades of relatively slow growth, both labor productivity and total factor productivity showed strong acceleration in the late 1990s. Chart 1 plots the average annual growth rate of labor productivity for the U.S. nonfarm business sector, where annual labor productivity growth averaged 2.67% for 1995-2000, compared to 1.35% percent for 1973-95 and 2.87% for 1947-73. Total factor productivity growth (not shown) experienced a similar acceleration, with the annual rate of growth rising to 1.26% for 1995-98, from 0.40% for 1973-95 and 1.87% for 1948-73 according to the Bureau of Labor Statistics (BLS, (2000a, 2000b)).

Over the same period, U.S. firms continued their massive investment in information technology (IT) assets, defined here to include business investment in computer hardware, computer software, and telecommunications equipment.[3] In 1999 alone, U.S. firms invested $373B in these three assets, which accounted for more than 30% of all nonresidential fixed investment. This massive investment is due in part to the relative price declines in these assets, particularly computer hardware.[4] As a result, the stock of IT capital has grown much faster than other forms of capital, e.g., 22.4% per year for 1989-99 for computer hardware vs. 2.5% for private fixed assets, and IT reached nearly 9% of business fixed capital in current dollars in 1999. Finally, it is worth mentioning that the pace of quality change for IT assets has accelerated in recent years. The quality-adjusted price of computer hardware, for example, fell 14.6% per year for 1990-95, but 27.7% for 1995-99.

b. The Emerging Consensus

This combination of accelerating quality change in IT, rapid investment, and strong productivity growth in the late 1990s has received considerable attention. BLS (2000b), Council of Economic Advisors (CEA, 2001), Jorgenson and Stiroh (2000), Oliner and Sichel (2000), and Whelan (2000a) have all quantified the relationship using a traditional "growth accounting" methodology and have reached a qualitatively similar conclusion that IT has played a key role in the U.S. productivity revival.

This approach is well-known and employs a growth accounting identity like:

$$(1) \quad d\ln V \equiv \bar{v}_{K_{IT}} d\ln K_{IT} + \bar{v}_{K_N} d\ln K_N + v_L dnL + d\ln A$$

where V is aggregate real output (value-added), K_{IT} is the flow of capital services from IT, K_N is the flow of capital services from other capital inputs, L is labor input, A is total factor productivity. $\bar{v}$ represents the nominal share of the subscripted input in total output and are measured so that $\bar{v}_{K_{IT}} + \bar{v}_{K_N} + \bar{v}_L = 1$.

As summarized in Table 1, these studies show two IT-related forces were driving the acceleration in productivity in the late 1990s relative to the prior two decades. The first force is productivity gains in the production of IT, measured as accelerating TFP growth in the IT-producing industries. This accounted for about 25% of the approximately 1 percentage point acceleration

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[3]The broader definition of "information processing equipment and software " employed in the NIPA is not used here since many of these additional assets are not experiencing rapid quality improvement and are not associated with explicit constant-quality deflators in the NIPA. See Jorgenson and Stiroh (2000).
[4]See Tevlin and Whelan (2000).

according to both Jorgenson and Stiroh (2000) and Oliner and Sichel (2000).[5] The second force reflects the rapid IT investment and IT-related capital deepening. Here too, the contribution to the productivity acceleration is quite large, ranging from 0.50 percentage point in Oliner and Sichel (2000) to 0.38 percentage point in BLS (2000b) and 0.34 percentage point in Jorgenson and Stiroh (2000). Based on different model of obsolescence, Whelan (2000a) reports an even larger contribution from computer capital. Despite conceptual and methodological differences, the common conclusion is that both the *production* and the *use* of IT have made important contributions to the U.S. productivity revival. Note that Gordon (2000) attributes 0.50 percentage point to cyclical forces and 0.14 to measurement effects, so that he estimates a much smaller acceleration in trend TFP growth.

This type of aggregate growth accounting study provides a valuable step toward understanding the impact of IT. By incorporating IT-related forces into a well-known framework, the impact of IT can be quantified in a straightforward fashion and compared to alternative explanations. Moreover, given the long lags in the availability of industry-level data, particularly capital stocks and gross output by industry, aggregate data is often the only avenue for addressing this type of productivity question in a timely fashion. Aggregate growth accounting studies of this type are not entirely satisfactory, however, and the remainder of this subsection discusses some important caveats about this approach.

One common criticism is that while growth accounting effectively quantifies the proximate sources of growth, it cannot provide a deeper explanation for why things happened.[6] In addition, a number of assumptions are required for the successful implementation of growth accounting calculations. For example, the assumptions of constant returns to scale and competitive markets are often imposed in the estimation of factor shares.[7] Finally, the use of factor shares to proxy for output elasticities essentially assumes the results about the impact of capital. That is, as long as capital deepening occurs, there will be a measured contribution to growth, regardless of whether that capital actually contributes to production and there is no room for unproductive investment in this framework.[8] Thus, it is critical to also econometrically test for a link between IT-use and productivity gains to buttress the conclusions from growth accounting studies.

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[5]The Oliner and Sichel (2000) estimate refers to computer production plus computer-related semiconductor production. BLS (2000b) does not explicitly estimate the contribution from IT-production.
[6]See, for example, Grossman (1996).
[7]This is not always the case. The large literature inspired by Hall (1988, 1990) relaxes these assumptions and others. See Basu and Fernald (1995, 1997a, 1997b) for examples of a less restrictive growth accounting approach and Hulten (2000) for details on the assumptions as typically implemented.
[8]See Kiley (2000) for this type of critique. As an extreme example, consider what growth accounting exercises would show if firms invested heavily in an asset but then never actually use it for productive purposes. Growth

A second critique is that the intrinsic top-down nature misses much of the important variation among sectors. For example, Greenspan (2000) cautions that disaggregated data are needed to tie productivity performance to business practices. Since both productivity growth and IT intensity vary enormously among component industries and firms, part of the impact of IT may be missed by aggregate studies. This type of heterogeneity has been an important part of the plant-level work that is based on the Longitudinal Research Database (LRD), e.g., Baily, Hulten, and Cambell (1992) and Haltiwanger (1997), as well as industry studies, e.g., Basu and Fernald (1997a, 1997b).[9]

Wide heterogeneity offers one explanation for why earlier research on the economic impact of IT at disaggregated levels typically found a substantial impact, while earlier aggregate studies did not. For example, firm- or industry-level studies by Brynjolfsson and Hitt (1995), Lichtenberg (1995), Steindel (1992) report a large and significant impact of IT, while earlier aggregate studies did not (Oliner and Sichel (1994) and Jorgenson and Stiroh (1995, 1999)). While this can be reconciled by the relatively small aggregate IT capital shares in the 1980s and early 1990s, it is also possible the productive impact of IT became obscured at higher levels of aggregation when IT-intensive industries were combined with less intensive ones. McGuckin and Stiroh (2000b), for example, found that the estimated output elasticity of computers is typically larger when more disaggregated data are employed.

Despite these limitations, strong results from the aggregate growth accounting studies are now driving the emerging consensus that IT is having an important impact of U.S. productivity growth. Some disagreement remains, however, and the following section discusses these alternative views.

c. Alternative Views of the Economic Impact of IT

Most notably, Gordon (1999, 2000) has argued that much of the U.S. productivity acceleration can be traced to two factors – a normal, cyclical acceleration of productivity as the economy expands above trend and strong productivity growth in the production of IT. The implication is that the productivity revival is not particularly broad-based, and certainly not the result of the massive investment in IT in throughout the IT-using economy. Rather, IT investment may be focused on unproductive activities like market share protection, duplication of existing operations, or on-the-job consumption (Baily and Gordon (1988), Gordon (2000)).

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accounting would observe this capital deepening effect, measure a contribution from capital, and then, since output growth is fixed, measure a smaller total factor productivity residual. This is the intuition behind Gordon's (2000) critique of the productive impact of IT.

[9] See Bartelsman and Doms (2000) for a recent discussion of the LRD literature.

Both points are surely valid to some degree. A cursory examination of the productivity data, in terms of both labor and total factor productivity, show clear procyclicality. Basu and Fernald (1999) report a correlation between total factor productivity and output of 0.8, which they attribute primarily to variable utilization rates and resource reallocation between industries. In terms of the IT-producing industries, again the data are quite clear. BLS (2000a) reports that total factor productivity growth in two high-tech producing industries – industrial machinery and equipment (SIC #35), and electronic and other electric equipment (SIC #36) – was 7.6% and 7.2% per year for 1995-98, respectively. In contrast, average growth rates were only 2.5% for manufacturing as a whole and 1.3% for the nonfarm business sector. Labor productivity growth rates are even higher.

To be precise about this view, consider the estimates in Gordon (2000, Table 2). When durable goods manufacturing is excluded (nonfarm, nondurables), he estimates trend productivity growth of 1.13% per year for 1972-95. More recently, actual productivity for this sector was 1.99% for 1995-1999. Of this 0.86 percentage point acceleration, 0.63 was attributed to cyclical effects, 0.14 to methodological changes to prices, 0.05 to labor quality effects, and only 0.04 to an acceleration in trend labor productivity. Thus, trend labor productivity appears essentially unchanged outside of durable goods manufacturing despite the massive investment during the IT revolution.

A further decomposition by Gordon uses a 0.33 contribution from capital deepening, which implies a 0.29 percentage point *deceleration* in trend total factor productivity growth in the nonfarm, nondurable sector since 1995. While trend total factor productivity growth may have actually slowed, Gordon implies that it is more likely that the growth accounting methodology incorrectly attributed too large a contribution to computers. This suggests "computer investment has had a near-zero rate of return outside of durable manufacturing (Gordon 2000, pg. 57)."

While suggestive, some caution is warranted. As with other aggregate studies, this decomposition cannot really isolate productivity gains in the most IT-intensive industries since it only looks at relatively aggregated data. The nonfarm, nondurable sector is enormous, producing nearly 90% of 1999 GDP. Moreover, it contains a large number of heterogeneous industries, some of which are very intensive IT-user and some of which are not. Only by looking at the productivity performance of the individual industries can one really get at the impact of IT.

A second alternative view comes from Kiley (1999, 2000) who argues that adjustment costs have contributed to some negative findings on IT and productivity. This view goes farther than arguing that IT-use has not increased productivity by concluding that adjustment costs create frictions that can actually cause investment in IT capital to be *negatively* associated with productivity, at least contemporaneously. Kiley (1999) concludes these adjustment costs are quite large, responsible for a

0.5 percentage point decline in measured total factor productivity growth in the 1980s and early 1990s, while Kiley (2000) reports low or negative short-run returns to computers in firm-level data. The recent resurgence of productivity in late 1990s could reflect the economy's approach to a steady-state where adjustment costs fade, but as mentioned above, investment in IT has accelerated in recent years so one might expect large adjustment costs to continue which seems inconsistent with the U.S. productivity revival.

A third alternative view comes from Roach (1998), who argues that much of the productivity revival is a statistical artifact as the secular trend toward service-related industries has generated increased mismeasurement of labor hours. Moreover, he argues that IT facilitates this measurement error by allowing increased flexibility of work and longer effective workdays that are not captured by the official statistics. Thus, actual labor hours in the IT-intensive industries may be understated, and therefore productivity growth overstated. While certainly possible, this mismeasurement story cuts both ways. Dean (1999), for example, reports the BLS position that inputs are relatively well measured and it is output that suffers from the most intense measurement problems due to the introduction of new goods, quality change, and inadequate prices for parts of the non-manufacturing economy. Evaluating this issue seems to require and industry-by-industry assessment of the data, and is not pursued here.[10]

The remainder of this paper examines the link between IT investment and the U.S. productivity revival by moving beneath the aggregate data to examine variation in productivity performance and IT-intensity across U.S. industries. This analysis augments the recent growth accounting studies by examining the statistical correlations between IT-use and productivity growth in the recent period of the U.S. productivity revival.

III. Productivity Concepts and Data

This section outlines the basic concepts and data used. As mentioned above, the focus is on labor productivity; this choice reflects a combination of conceptual and practical factors. Conceptually, the primary effect of IT-use in a neoclassical world is on labor productivity through traditional capital deepening effects (Baily and Gordon (1988), Stiroh (1998), Jorgenson and Stiroh (1999), and others). In this case, IT is not viewed as a special type of capital, but rather as a traditional piece of equipment in which firms invest that raises the productivity of labor. Total factor productivity gains should be seen only in the production of IT, where true technological progress allows the production of improved capital goods at lower prices.

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[10]See Triplett and Bosworth (2000) for work in that direction.

It is possible, of course, that total factor productivity might be affected by IT-use through production spillovers or externalities, e.g., Bresnahan (1986) and Bartelsman et al. (1994). Alternatively, some have argued that IT investment represents "embodied technological change," a force distinct from capital deepening, e.g., Greenwood et al. (1997). Differentiating between these forces, however, is quite difficult and subject to potentially severe measurement problems.[11] By focusing on labor productivity, one can gauge the impact of IT without making the difficult, and sometimes semantic, distinction between traditional capital deepening, embodied technological change, and productivity spillovers.

There are also practical reasons to focus on labor productivity. The basic data required to estimate labor productivity growth, real output and some measure of labor input, are available much more quickly and at a more disaggregated level than the data needed to correctly estimate total factor productivity. For example, BLS (2000a) released total factor productivity estimates through 1998, but only for economy aggregates and manufacturing industries. One could estimate a crude measure of total factor productivity with the data at hand, but this would be a rough approximation.

a. Measuring Productivity

(i) Basic Definitions

The standard industry production model is based on a gross output production function that relates industry gross output to the primary inputs, (capital and labor), intermediate inputs (like energy and materials purchased from other industries), and total factor productivity as:

$$(2)\quad Y_i = f(K_i, H_i, M_i, Z_i)$$

where Y is real gross output, K is capital, H is hours worked, M is intermediate inputs, and Z is a total factor productivity index, all for industry i. Time subscripts have been suppressed.[12]

Alternatively, one could employ a value-added or gross product originating (GPO) concept for output that depends only on the primary inputs as:

$$(3)\quad V_i = f(K_i, H_i, Z_i)$$

where V is real value-added.

Average labor productivity, *ALP*, is defined simply as real output per hour worked:

[11]See Griliches (1995) for more on this point in the spillover context

[12]This very simple representation abstracts from utilization issues, e.g., the workweek of capital or labor effort, adjustment costs, and labor quality effects. See Basu et al. (2000) for a more fully developed production function.

$$
(4) \qquad \begin{aligned} ALP_i^Y &= Y_i / H_i \\ ALP_i^V &= V_i / H_i \end{aligned}
$$

where a Y superscript indicates gross output and a V superscript indicates value-added.

Economic theory and the empirical evidence show that gross output is the proper output concept for productivity analysis. Conceptually, firms and industries actually produce gross output, say shoes, from some combination of primary and intermediate inputs, say capital, labor, leather and electricity; the production model should match this as closely as possible. Value-added, on the other hand, is an artificial construct that reflects only primary inputs and therefore does not correspond to a well-defined output concept at the industry level. Moreover, only under specific assumptions about the separability of primary inputs from intermediate inputs does a value-added production function exist and provide a valid description of the underlying production technology.[13]

One difficulty that gross output creates, however, is a conceptual disconnect from the aggregate productivity series. That is, aggregate measures of output are typically a value-added concept, while industry measures of output are more appropriately defined using a gross output concept. This makes aggregation and disaggregation somewhat cumbersome and involves "reallocation effects" due to movement of resources between industries, e.g., Jorgenson et al. (1987) and Basu and Fernald (1997a, 1997b). This issue is addressed further in Section V.

(ii) Production Function Estimates

One can be more precise about how production factors determine labor productivity growth. For example, one can examine how different types of capital affect labor productivity growth of those industries that make the investments, e.g., a Cobb-Douglas gross output production function that explicitly decomposes capital into a IT-related and non-IT related portion. Taking logs and differencing yields the familiar productivity growth relationship:

$$
(5) \quad d \ln ALP^Y = d \ln y = \alpha_{IT} d \ln k_{IT} + \alpha_N d \ln k_N + \beta d \ln m + d \ln z
$$

where lower-case variables are per hour worked, α_{IT} is the output elasticity of IT-capital, α_N is the elasticity of non-IT capital, and β is the output elasticity of intermediate inputs. Note that constant returns to scale are not imposed here. Industry and time subscripts have been suppressed.

If there are constant returns, competitive markets, and no input utilization issues, then this can be implemented as a growth accounting equation where elasticities are estimated from cost shares and

[13]See Norsworthy et al. (1983) and Jorgenson et al. (1987) for empirical rejections of this assumption. More recently, Basu and Fernald (1995, 1997a, 1997b) show that value-added data lead to biased estimates and incorrect inferences about production parameters.

the growth of total factor productivity ($d \ln z$) is calculated as a residual. If the neoclassical assumptions fail to hold, however, then the observed cost shares could be poor proxies for the true output elasticities.

Those assumptions can be relaxed and Equation (5) estimated econometrically to quantify the impact of input growth on productivity growth, e.g., Hall (1990), Basu and Fernald (1995, 1997a), and others have done this in specifications without the IT/non-IT breakdown. Berndt and Morrison (1995), Brynjolfsson and Hitt (1995), Gera et al. (1999), Lichtenberg (1995), Lehr and Lichtenberg (1999), McGuckin and Stiroh (2000b), and Steindel (1992) have estimated a version of Equation (5) focusing on the impact of IT.

b. Measuring Capital

The proper measure of capital input, i.e., capital stocks versus the flow of capital services, is an important issue in the successful estimation of Equation (5). As originally implemented by Jorgenson and Griliches (1967), this conceptual difference largely reflects the proper technique to form aggregates of capital. Assuming that one wants to avoid substitution biases and be consistent with the output data, this requires some type of chain-weighted index, e.g., a Tornqvist or Fisher Ideal index. Once the index is chosen, the distinction between capital stocks and capital services is essentially an issue about how to properly weight heterogeneous capital inputs to form an aggregate index.

Capital stock indices use acquisition prices as weights, while capital services indices use rental prices as weights. For example, using a Tornqvist index for aggregation, aggregate capital stock, K^{Stock}, and aggregate capital service, $K^{Services}$, could be estimated as:

$$d \ln K^{Stock} = \sum_j \overline{w}_j d \ln K_j, \qquad w_j = \frac{P_j K_j}{\sum_j P_j K_j} \tag{6}$$

$$d \ln K^{Services} = \sum_j \overline{v}_j d \ln K_j, \qquad v_j = \frac{c_j K_j}{\sum_j c_j K_j}$$

where P_j is the acquisition price, K_j is the installed stock of capital, c_j is the rental price, all for asset j. w_j and v_j are the shares of capital stock and services for each asset, respectively, and a bar indicates a two-period average.[14]

[14]In practice, it is often assumed that capital takes some installation period to become productive, so that some combination of the current and lagged growth rate would enter the capital services aggregation equation. See Jorgenson and Stiroh (2000) and Oliner and Sichel (2000) for details.

The estimation of the rental price accounts for the factors thought to determine the marginal cost of using a piece of capital equipment, e.g., tax, depreciation, opportunity costs, and capital gains/losses on particular assets, and thus determine the relative marginal products of each type of capital. IT assets, for example, are typically associated with high depreciation rates and large capital losses so that they have relatively large service price weights. Since these assets are also growing faster than other forms of capital, this leads aggregate capital services to grow faster than aggregate capital stock in recent years. See Jorgenson and Stiroh (2000) for details on estimating capital services and differences across assets.

c. Data

(i) BEA Gross Product Originating Data

This analysis requires substantial data, including real gross output, labor inputs, capital inputs, and intermediate inputs, all for each industry and over time. Most of this data are all available at the aggregate, broad private sector (one-digit SIC codes), and detailed private industry (roughly two-digit SIC codes) in the GDP by industry or "gross product originating (GPO)" data that comprise gross domestic income and are maintained by the Bureau of Economic Analysis (BEA). Lum and Moyer (2000) summarize the recent data and Lum et al. (2000) provide details on the data construction and sources.

This data now include nominal and chain-weighted gross output for 62 detailed industries for 1987-99 and for a subset of industries for 1977-99. In addition to gross output data, the data contain value-added (in current and chain-weighted dollars), estimates of labor income and capital income, various measures of the quantity of labor like full-time equivalent employees (FTE), and intermediate inputs (in current and chain-weighted dollars). Hours are not available and FTE are used as the measure of labor input throughout. I combine two real estate-related industries into a single industry, leaving 61 detailed industries with gross output data.

Note that BEA includes the statistical discrepancy in its estimate of "private industries," where the statistical discrepancy is defined as GDP expenditures less gross domestic income. Since BEA views the expenditure side data as more reliable, the statistical discrepancy is added as an "industry" to the gross domestic income (value-added) accounts. In the productivity analysis that follows, I drop the statistical discrepancy component in all years since it is impossible to align it with measured inputs. Since the statistical discrepancy has been falling in recent years, BEA's aggregate of private sector value-added grows more slowly than an aggregate over the private sectors that excludes the statistical discrepancy.

(ii) BEA Capital Stock Data

The second major piece of data comes from the "Tangible Wealth Survey" (BEA (1998)). This data provide information on 57 distinct types of capital goods in current and chain-weighted dollars for 62 industries from 1947 through 1996. The 57 distinct types of assets for each industry are aggregated into three broad types of capital – IT, other equipment, and structures – for both capital stocks and my estimates of capital services for each industry. The level of asset aggregation is somewhat arbitrary, and one must balance aggregation and tractability concerns.[15] I define IT capital to include seven types of computer hardware (mainframes, personal computers, direct access storage devices, printers, terminals, tapes drives, and other storage devices) and communications equipment. Other equipment includes all other types of fixed business equipment investment like industrial machinery, automobiles, engines, etc. Structures include all types of nonresidential structures. Land and inventories are not included.

While the GPO data and capital stock data are both from the BEA and both break out 62 distinct industries, they are not the same industries. For example, the GPO data only have an aggregate of electric, gas, and sanitary services, while the capital stock data provide details for each of the three components. These data were aggregated to form 57 industries with both output and capital data. Appendix Table A lists 61 industries with output data, the 57 industries with both gross output and capital stock data, the broader sector to which they belong, and the 1996 value of gross output and total capital stock. The 57 distinct types of capital assets and the aggregate value across all industries are listed in Appendix Table B.

All aggregation is done via Torqvist indices. For industry capital services, asset-specific rental prices are taken from Jorgenson and Stiroh (2000). While this misses industry-level variation in certain terms of the service price equation, e.g., asset-specific capital gains vary across industries since industries purchase different mixes of each asset, it does capture the dominant features of the service price equation and should provide a good estimate of capital services using reasonable aggregation weights. For industry capital stocks, industry- and asset-specific acquisition prices are taken directly from the Tangible Wealth Survey.

Two data limitations deserve mention. First, the capital data are currently available only through 1996. Since the recent productivity revival began in 1995, relatively old capital data are a constraint and somewhat hinders the analysis. Second, these data were created before the benchmark revision of the NIPA in 1999, so software is not treated as a distinct investment good. This should not

[15]McGuckin and Stiroh (2000b) show that inappropriately aggregating equipment and structures can cause problems for production function estimates.

be too large of a problem, however, since computer capital accumulation and software accumulation are likely to be highly correlated across industries.

IV. IT and the U.S. Productivity Revival across Industries

The section addresses the two empirical questions described above. First, is the U.S. productivity revival widespread or is it concentrated in relatively few industries? This question directly affects the strength and stability of the recent productivity revival. If all the gains were concentrated in a single industry, for example, then a relatively narrow disruption could unhinge the entire productivity revival. In addition, the breadth of the productivity revival has implications for the distribution of income and wealth; if productivity gains are highly concentrated, one might expect wage gains or rents to capital-owners to also be highly concentrated. While this question is not an IT-question per se, it should be of interest in its own right.

Second, can these industry productivity gains be linked to IT? By quantifying the productivity gains associated with IT, this sheds light on the returns to the massive IT investment. For example, if IT is used largely to reallocate market share between firms, then this might entail no industry gains and no net benefit for society. On the other hand, if IT investment raises productivity through traditional capital deepening channels or production spillovers, then this enlarges the production possibility frontier for the society as whole. The impact of IT-use also has implications for U.S. international competitiveness, e.g., Gust and Marquez (2000) report that most industrialized countries have not experienced a productivity revival like the U.S., which they attribute in part to lower IT investment shares in those countries.

a. Is the Productivity Revival Widespread?

I first consider the appropriate breakpoint for dating the productivity revival. Earlier studies by BLS (2000a), Gordon (2000), Jorgenson and Stiroh (2000), and Oliner and Sichel (2000) assume a breakpoint in 1995. Casual examination of the time series data suggest this is reasonable, but Hansen (1992) points out the pitfalls of choosing and testing for breakpoints after the data have been examined. A useful first step, therefore, is to econometrically estimate an unknown break point in the aggregate productivity aggregate data.

Hansen (1997) provides a means to identify a structural break and then test for the significance of the change.[16] I use this methodology to identify breaks in productivity growth for the business sector, the nonfarm business sector, and manufacturing sector using quarterly data from 1974:Q1 to

[16]This work builds on Andrews (1993) and Andrews and Ploberger (1994) and provides numerical approximations to the distribution of the test statistics.

2000:QIII.[17] The results for the business and nonfarm business sector data indicate a breakpoint of 1995:QIII, essentially the same as used in the aggregate studies. The asymptotic p-values of the Andrews/Quandt test, however, are only marginally significant at 0.11 for the business sector and about 0.14 for nonfarm business sector. For manufacturing, the estimated breakpoint is 1993:III and is highly significant (p=0.01). While not overwhelming evidence, these tests suggest that something structural did change around 1995. Since the industry-level data are available only at an annual frequency, I use the business sector breakdate and follow earlier studies by identifying year-end 1995 as the beginning of the productivity revival.

Table 2 presents summary statistics for productivity growth for 1995-99 compared to the earlier periods 1987-95 and 1977-95.[18] I begin with aggregate productivity growth using several different output concepts and aggregation levels. For the value-added concept, I report average productivity growth based on GDP, BEA's private industries aggregate which includes the statistical discrepancy, and a sector aggregate of private industries that does not. For the gross output productivity concept, I only report an aggregate of the private sectors, since there is not a meaningful GDP analog and no statistical discrepancy.

The value-added productivity acceleration for 1995-99 less 1987-95 for private industries is about 1 percentage point when the statistical discrepancy is included (BEA), 1.4 percentage points when it is not (Sector Aggregate), and 1.2 percentage points for the gross output concept. The BEA version of private industries shows slower productivity growth than the sectoral aggregate in recent years because the statistical discrepancy became increasingly negative and it is included in the BEA's private industry aggregate. These are all quite close to the BLS estimates for the nonfarm business sector, so the labor productivity analysis based on these BEA numbers is comparable and not an artifact of this data.

Table 2 also reports the gross output productivity acceleration for the 10 broad sectors, where I follow the BEA's sectoral convention except that durable good manufacturing and nondurable goods manufacturing are split into distinct sectors. Productivity acceleration varies considerably across

[17]I use a simple model where productivity growth equals a constant that is allowed to change once during the sample period. The Andrews/Quandt "sup" test identifies a specific estimate of the breakdate as the maximum value of the Lagrange multiplier statistic of the null of no structural change between any two periods, while the Andrews and Ploberger "exp" and "ave" tests use the entire series of the multipliers. The last two tests do not identify a specific breakdate, but provide additional information about the significance of an estimated break. Note that the use of only post-1973 data assumes an earlier break at that point.

[18]These periods are chosen for the following reason. 1995 is generally seen as the beginning of the U.S. productivity revival and consistent with the econometric tests discussed above. 1987 and 1977 reflect the availability of data in the GPO database. I do not report a comparison with 1990-95, since 1990 was the beginning of a recession, but the results are similar.

sectors, ranging from -1.25 percentage point in agriculture to 2.50 percentage points in durable goods manufacturing when 1995-99 is compared to 1987-95. CEA (2001) and Nordhaus (2000) report a broad productivity acceleration with wide variation across major sectors using a *value-added* concept.

These raw data point to a broad productivity revival. While it is clear that the durable goods sector showed particularly large gains in the late 1990s, it is also clear that it is not the only sector to show improvement. Eight of the ten sectors show a productivity acceleration, and the two that don't, agriculture and mining, are relatively small, accounting for only 2.5% of 1999 GDP. Thus, at first glance, it appears that the productivity revival is relatively broad-based in the sense that the vast majority of the U.S. economy shows productivity gains in the late 1990s.

Table 2 also provides summary statistics for gross output productivity growth for the 61 detailed industries. Again, these data suggest a relatively broad productivity revival – the mean and median increase for 1995-99 vs. 1987-95 were 1.09 percentage points and 0.60 percentage point, respectively. Relative to a longer earlier period 1977-95, the 49 industries with data for both periods show a mean acceleration of 1.19 percentage point and a median gain of 0.99 percentage point.[19]

At this point it is useful to examine the industry productivity data more directly. Chart 2 plots the 1995-99 growth rate vs. the 1987-95 growth rate for the 61 industries. Points above the line show accelerating productivity growth, while those below the line show decelerating productivity growth. The majority of industries – 38 out of 61 industries – show a productivity acceleration, again suggesting a broad productivity revival.

Four outliers stand out and deserve special mention. Two of these are high-tech producing industries (industrial machinery and equipment (SIC #35) and electric and other electronic equipment (SIC #36)) and two are finance-related (security and commodity brokers (SIC #62) and holding and other investment offices (SIC #67)). The high-tech industries show gains due to the fundamental technological advances in the production of IT, while the finance-related gains may be an artifact of how output, and therefore productivity, are measured in those industries.[20] Subsequent econometric work will be careful about whether these industries are driving results.

While the raw data show that most industries experienced accelerating productivity growth in the late 1990s, it is useful to gauge the significance of the acceleration by with a simple test of a change in the mean growth rate across industries:

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[19]Real gross output data is not available prior to 1987 for nine industries and six industries are combined into three industries in the early period, which accounts for only 49 industries having data for the full period 1977-99.

[20]Real gross output for security and commodity brokers is calculated as commissions, underwriting profits, securities sales, trading accounts, etc., deflated by various securities-related implicit price deflators. For holding

$$(7) \quad d \ln A_{i,t}^{Y} = \alpha + \beta D + \varepsilon_{i,t}, \quad D = 1 \; if \; t > 1995, D = 0 \; otherwise$$

where the estimate of α gives the mean prior to 1995 and β the mean acceleration, *t* is either 1977-98 or 1987-1998, and *i* is industry. Since it is unlikely that errors are homoskedastic or uncorrelated across industries, standard errors are corrected for heteroskedasticity and to allow for correlation between industries within the same sector.

Table 3 presents results for various estimates of Equation (7). The first column is a simple OLS regression, which shows the mean acceleration of 1.09 percentage points for all 61 industries, although it is not significantly different from zero (p-value=0.14).[21] When the longer period 1977-95 is compared, the acceleration is a significant 1.19 percentage points. This implies a meaningful acceleration of productivity growth for the typical industry that is not driven by a few outliers.

Results from a more appropriate analysis with industries weighted by relative size (measured as full-time equivalent employees (FTE)) are reported in the second column. Here, there is a large and significant acceleration in both periods.[22] As further robustness checks, the regression is estimated without the previously mentioned four outlier industries and without all industries in durable goods manufacturing. The coefficient falls in size since these industries show large productivity gains, but the acceleration remains economically large and statistically significant. For example, the mean acceleration for a non-outlier industry outside of durable goods manufacturing was 0.73 percentage point when 1995-99 is compared to 1987-95 and 1.00 percentage point when compared to 1977-95.[23]

It is important to point out that there is no attempt to cyclically adjust these data; all analysis is done using actual data as reported by BEA. This reflects the idea that this productivity acceleration is somewhat different from earlier periods of rising productivity growth. As can be seen in Chart 1, most of the post-war periods of rising productivity growth have occurred after recessions, while the recent productivity acceleration has occurred very late in this economic expansion. If productivity is typically procyclical due to variable utilization and resource reallocation effects, e.g., Basu and

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and other investment offices, real gross output is calculated as the sum of GPO plus an extrapolated intermediate input series, deflated by a composite cost-based price index. See Lum et al. (2000) for details.

[21]This lack of significance should not be too much of a worry. Dropping the tiny private household industry with a 1999 GDP share of 0.1%, for example, raises the estimated mean acceleration to 1.20 (p-value=0.09).

[22]Output weights, in terms of either gross output or value-added, give qualitatively similar results. FTE weights are reported since they are the more natural aggregation weights. Also, robust regressions where weights are determined endogenously based on the size of the error term yield similar results.

[23]As final robustness checks, one can test the acceleration of productivity growth using non-parametric methods. I test whether the median acceleration of productivity growth is zero for both comparison periods. The null hypothesis that median productivity growth in the later period is less than or equal productivity growth in the

Fernald (1999b), then one would expect these forces to have largely worked their way out during the nine-year expansion. Yet, productivity growth is actually accelerating, suggesting a different process. Basu, Fernald, and Shapiro (2000) conclude that the recent productivity acceleration stems from faster technological change, and not from temporary factors like factor utilization and factor accumulation.

In addition, it is quite difficult to separate trend and cyclical components, particularly when the data end in the middle of the cycle, as is currently the case. Moreover, since the focus of this paper is on industry-level trends, estimating distinct cyclical adjustments for each individual industry would likely introduce considerable noise into the analysis. Finally, in contrast to earlier periods of economic recovery and productivity acceleration, growth in nominal GDP for 1995-98 was not particularly strong suggesting that productivity gains were a driving force and not the result of increased aggregate demand as in earlier periods of cyclical productivity gains. Thus, it may be inappropriate to use old information on cyclical adjustments for this recent period.

With this caveat in mind, the data clearly show a productivity revival that is broad-based, and not limited to the industries that produce IT or other durable goods manufacturing industries.[24] A variety of specifications show a significant acceleration in productivity growth for the typical industry during the late 1990s. While the question of whether these gains should be attributed to cyclical forces or the underlying trend is not addressed, the recent productivity revival is clearly not limited to only a few industries.

b. Is the Productivity Revival Linked to IT?

The second question is whether these observed productivity gains can be linked to the use of IT, which I address with several complementary empirical approaches. First, "difference-in-difference" style tests are used to compare the productivity acceleration of IT-intensive industries to other industries as in McGuckin and Stiroh (2000a). Second, I extend this approach and estimate several additional specifications that link variation in IT to productivity growth. Finally, production functions are estimated using the generalized method of moments (GMM) methodology developed by Blundel and Bond (1998a, 1998b).

(i) Difference-in-Difference Estimates

One way to examine the impact of IT is to compare the productivity acceleration of the IT-intensive industries to the other industries. That is, did IT-intensive industries show larger

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early period is strongly rejected when one examines the complete set of industries or if one drops the IT-producing industries and the FIRE outliers.

[24]Looking at value-added productivity, Nordhaus (2001) also concludes that the U.S. productivity revival is not narrowly focused in a few sectors that produce It.

productivity gains than other industries? If IT accumulation is a driving force behind faster productivity gains then the industries that use IT most intensively should show the largest productivity acceleration. Alternatively, if the U.S. productivity revival is largely a cyclical phenomenon driven by strong aggregate demand throughout the economy, gains should be independent of IT-use and one would expect all industries to show comparable gains.

This comparison can be done by extending the test for difference in means in Equation (7) with an additional interaction term that identifies IT-intensive industries as in the following difference-in-difference style regression:

$$\begin{aligned} &d \ln A_{i,t}^{Y} = \alpha + \beta D + \gamma C + \delta D \cdot C + \varepsilon_{i,t}, \\ (8) \qquad &D = 1 \; if \;\; t > 1995, \; D = 0 \; otherwise \\ &C = 1 \; if \;\; IT - intensive, \; C = 0 \; otherwise \end{aligned}$$

where α is the mean growth rate for non IT-intensive industries in the period prior to 1995, $\alpha+\gamma$ is the mean growth rate for IT-intensive industries prior to 1995, β is the acceleration for non-IT intensive industries, $\beta+\delta$ is the acceleration for IT-intensive industries, and δ is the differential acceleration of IT-intensive industries relative to others. Standard errors are again corrected for heteroskedasticity and for correlation of industries within sectors.

The main issue here is how to define an IT-intensive industry. Ideally one wants an exogenous indicator of IT-intensity prior to the productivity revival. That is, both the dependent and independent variable should not be defined over the same period since they would likely be subject to the same shocks, e.g., strong demand, and would suffer from simultaneity bias. Therefore, I define IT-intensity based on alternative variables in 1995. By defining IT-intensity in the period prior to the productivity revival, I hope to identify the impact of variation in IT accumulation on subsequent productivity growth. Of course, industries that expected future demand increases and productivity gains may have invested in IT in anticipation of these changes, so this is not a perfect control.

IT-intensity can be defined in a number of ways; natural choices include the share of IT capital in total capital, the ratio of IT capital to output, or IT-capital per worker.[25] My preferred measure is the share of IT capital services in total capital services since this indicator identifies those industries that expend a considerable portion of their tangible investment resources on IT and are reallocating their resources toward high-tech assets. The IT capital to output ratio is not ideal since IT capital (and value-added in general) varies so much across industries; IT could appear relatively

[25]All capital and output numbers are estimated via chain-weights, so it is inappropriate to compare levels of chain-weighted dollars. Therefore, all ratios are measured in terms of nominal dollars. See Whelan (2000b) for details.

unimportant if intermediate inputs are large. IT capital per worker is not ideal since it is likely to suffer more from endogeneity problems since it includes the same denominator as the labor productivity variable. As robustness checks, however, I compare estimates using all three metrics, as well as a composite indicator for those industries identified as IT-intensive by any two of the three indicators. In all cases, an IT-intensive industry is defined as one with a 1995 indicator variable above the 1995 median for all industries. Later tests use the continuous variable.

Before proceeding to the regression results, it is useful to describe the IT-intensity indicators, which show wide variation across industries. For example, the nominal IT capital services share in total capital ranges from 0.03% in farms to 58% in telephone and telegraphs, with a mean of 10.2% and a standard deviation of 12.6% in 1995. Similar variation holds for the other IT-intensity indicators. All three measures are highly correlated with simple correlations in the 0.7-0.9 range.

The first three columns of Table 4 report estimates of Equation (8) for all 57 industries using the three alternative indicators of IT-intensity defined above, while the fourth column uses the composite index.[26] The next three columns are robustness checks that use the preferred indicator of IT-intensity, the IT share of capital, but include only subsets of industries that drop the outliers (the two IT-producing industries and the two finance-related industries) identified above. All regressions are weighted using FTE as weights and standard errors are corrected for heteroskedasticity and to allow for correlation of errors across industries in the same sector.

The results suggest that IT-intensive industries experienced a larger acceleration of productivity growth than other industries.[27] For the first indicator, the 1995 IT share of capital, the IT-intensive industries show a significant 1.4 percentage points difference in productivity acceleration, but no significant difference in productivity growth rates for 1987-95. Interestingly, the non IT-intensive industries show essentially no acceleration in productivity growth. For the second indicator, the 1995 IT share of output, the differential acceleration is a bit smaller, 1.1 percentage points, but only marginally significant (p=0.14). It is quite large economically, however, putting the acceleration for IT-intensive industries three times that of other industries.

For the third indicator, 1995 IT capital per FTE, IT-intensive industries show faster productivity growth in the *earlier* period 1987-95, but no difference in terms of acceleration. Note,

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[26]Capital stock data are not available for four industries – social services, membership organizations, other services, and private households – so these industries are dropped from the remainder of the econometric work.

[27]The results are qualitatively similar when computers, rather than IT, are used to split industries. In addition, if the information from the three IT-intensity indicators are combined so that an overall IT-intensive industries is defined as one with an above-median score for any two of the three individual indicators, the results show a larger productivity acceleration for the IT-intensive industries. Results are slightly weaker when estimated without weights.

however, that these IT-intensive industries show a significant acceleration of productivity growth (e.g., 0.89+0.53=1.42, p-value=0.00), but it was not significantly different from other industries. This is reasonable: industries with high IT per worker in 1995 invested heavily in IT and/or reduced labor during the early 1990s, both of which contributed to faster productivity growth in the early period. Finally, using the composite index, IT-intensive industries show a productivity acceleration that is a significant 1.3 percentage points larger than other industries.

The last three columns of Table 4 use the preferred IT share of total capital services as the indicator of IT-intensity and show that the results are not entirely driven by the four productivity outliers in the late 1990s. In all cases, the productivity acceleration of the IT-intensive industries remains substantially larger than for other industries, although it is not significant when all four outliers are excluded (p=0.15).[28]

Taken together, the productivity experience of IT-intensive industries, however defined, appears quite different from other industries. Industries that invested heavily in IT in the early 1990s and increased the IT share of capital show significantly larger productivity gains than those that did not and industries with relatively high IT per worker experienced faster productivity growth during the earlier period. While could argue that this timing convention has not completely controlled for causality, IT capital appears to be an important part of the productivity revival across U.S. industries.

(ii) Alternative IT Regressions

The previous results show that IT capital is related to productivity growth, but the estimation framework was relatively restrictive. For example, all of the identification comes from one discrete variable chosen as the indicator of IT-intensity, which does not account for the wide variation in IT-intensity or allow the possibility that IT is correlated with other potentially important variables like other types of capital accumulation. To address these concerns, I estimate several broader, though still rather ad hoc, regressions that link recent productivity growth to earlier IT accumulation.

The first extension replaces the discrete IT-intensity indicator variable used in Equation (8) with the continuous variable that allows for differential effects depending on the degree of IT-intensity in the following regression:

$$\begin{aligned} d \ln A_{i,t}^{Y} &= \alpha + \beta D + \eta D \cdot IT_{95} + \varepsilon_{i,t}, \\ & D = 1 \; if \;\; t > 1995, D = 0 \; otherwise \end{aligned} \tag{9}$$

[28]Exclusion of the outliers does not substantively change the results using the alternative measures of IT-intensive (not reported).

where IT_{95} is one of the three IT-intensity variables defined above, normalized by subtracting the mean and dividing by the standard deviation. Thus, η represents the additional productivity acceleration for 1995-98 associated with a one standard deviation increase in 1995 IT-intensity.

The results, reported in Table 5, show a strong link between variation in IT-intensity and productivity acceleration. For example, a one-standard deviation increase in the 1995 IT share of capital is associated with a 0.8 percentage point productivity acceleration after 1995. This is true across all three measures, when the outlier industries are dropped, and when the actual variable rather than the normalized value enters directly (not reported). This supports the conclusion that industries that made the largest commitment to IT in the early 1990s experienced the largest productivity gains later on. Results are similar when estimated without weights (not reported).

While Equation (9) does not perfectly control for endogeneity or omitted variables concerns (industries that expected faster growth in the late 1990s may have invested in IT or other productivity-enhancing assets in the early 1990s), the results certainly point in the direction that IT affects productivity growth. I now consider an alternative specification that addresses both of these concerns.

Standard production theory links productivity growth to input accumulation and total factor productivity, e.g., Equation (5). In addition to the well-known simultaneity and omitted variable problems with this type of specification, this relationship could break down if the productive benefits of input accumulation take some time to achieve. Brynjolfsson and Hitt (2000b), for example, report that the returns to computers are larger over longer periods of time due to complementary activities undertaken by the firm, e.g., organizational change, that takes place over a period of several years. Kiley (2000) argues that adjustment costs and other friction lead to a negative, contemporaneous impact of IT accumulation, but a positive impact after some adjustment period.

One way to examine this issue is to estimate a broader specification that links average productivity growth for the recent period (1995-99) to average productivity and input growth for an earlier period (T_0-95) as:

$$\begin{aligned} d\ln y_{95-99} = {} & \beta_y d\ln y_{T_0-95} + \beta_m d\ln m_{T_0-95} + \\ & \alpha_{IT} d\ln k_{IT,T_0-95} + \alpha_{EQ} d\ln k_{EQ,T_0-95} + \alpha_{ST} d\ln k_{ST,T_0-95} + e \end{aligned} \tag{10}$$

where lower-case variables are per *FTE*, *Y* is real gross output, K_{IT} is IT-capital services, K_{EQ} is capital services from other equipment, K_{ST} is capital services from structures, and *M* is intermediate inputs. T_0 designates the beginning of the earlier comparison period and is set as T_0=1992, 1990, or 1987.[29]

[29]Note that these "long-difference" estimates effectively remove any industry-specific fixed effects.

The reduced form in Equation (10) provides a relatively tough test of whether IT is a good predictor of productivity gains. That is, including lagged productivity growth and input deepening should control for omitted variables and other contemporaneous factors that affect IT accumulation like expectations of future performance. Any remaining link between early IT accumulation and subsequent productivity growth then reflects real productivity gains associated with IT use.

Table 6 reports results for three early time periods (T_0=1992, 1990 or 1987) for two sets of industries – all 57 industries with capital data and the subset of 53 industries that excludes the IT-producing and FIRE outliers. Overall, IT capital appears to be very different from other forms of capital: lagged IT capital deepening always enters positively and is typically highly significant, suggesting that IT investment leads productivity growth. Moreover, the coefficient seems to get larger, the longer the lagged period. Industries that rapidly accumulated IT for longer periods of time show larger productivity acceleration in the subsequent period, a result similar to the firm-level evidence in Brynjolfsson and Hitt (2000b) and Kiley (2000).

Several other interesting results deserve mention. First, as expected, lagged productivity growth is a strong predictor of future productivity growth. Second, growth of other equipment per FTE is consistently negative and often significant. One interpretation is that industries that invested heavily in other forms of equipment misallocated resources and missed the potential productivity gains associated with IT. Alternatively, equipment may be a substitute for IT so that heavy IT investment is correlated with a reduction of other equipment investment as firms shifted toward high-tech assets. Finally, the coefficient on intermediate inputs varies considerably across regressions, suggesting no systematic relationship.

These results indicate that IT-capital differs substantially from other forms of purchased inputs. Of the major input classes, only IT-capital deepening is a significantly associated with future productivity acceleration. A likely explanation is that some lag is needed to successfully implement IT and reap the productivity payoff. Alternatively, firms may invest in IT in anticipation of future productivity gains, although this would require that firms utilize such information only for IT investment and not other types of capital. If it is the case that IT investment yields productivity gains only with a lag, this suggests continued productivity gains for the U.S. economy since IT investment accelerated in recent years. A final interpretation is that lagged IT investment is correlated with current IT investment. In this case, the regression is picking up a contemporaneous link with productivity growth rather than a lagged. However, it is interesting to note that only IT capital deepening seems to be a good predictor of future productivity gains. In any interpretation, the results indicate something different about IT capital and that IT matters for productivity.

(iii) Production Function Estimates

A final way to examine the productive impact of IT is to estimate industry-level production functions that explicitly account for the heterogeneity of capital inputs. Despite well-known econometric problems, e.g., simultaneity and omitted variables, this approach has a long history in economics in general, and in the IT-literature in particular. Berndt and Morrison (1995), Brynjolfsson and Hitt (1995), Kiley (2000), Lehr (1995), Lehr and Lichtenberg (1999), McGuckin and Stiroh (2000b), Siegel (1997), and Steindel (1992) have used various econometric specifications to examine the impact of IT on U.S. firms of industries. Brynjolffson and Yang (1996) and Brynjolfsson and Hitt (2000a) survey this literature.

This paper distinguishes itself from the earlier research in several important ways. First, I employ the generalized methods of moments (GMM) methods of Blundell and Bond (1998a) to account for simultaneity and omitted variable concerns. In contrast, earlier studies typically used simple OLS regressions, fixed effects frameworks, or less efficient instrumental variables methods.[30] Two, I utilize more appropriate estimates of capital service flows as the primary measure of capital. In contrast, earlier studies used less desirable measures of capital stock; in the firm-level studies, this was often a book value measure, which could differ significantly from the productive stock. Finally, all estimates are based on the conceptually more appropriate gross output production function, rather than the more commonly used value-added. Note, however, that the capital data are currently available only through 1996, so production function estimates only apply to 1996.

Following Blundell and Bond (1998b), I begin with a Cobb-Douglas production function that relates the log of output to observable inputs and errors:

$$\ln Y_{i,t} = \beta_M \ln M_{i,t} + \beta_L \ln L_{i,t} + \beta_{IT} \ln K_{i,t}^{IT} + \beta_{EQ} \ln K_{i,t}^{EQ} + \beta_{ST} \ln K_{i,t}^{ST} + \gamma_t + \left(\eta_i + \nu_{i,t}\right) \tag{11}$$

where Y is output, M is intermediate inputs, L is labor, K^{IT} is IT capital input, K^{EQ} is other equipment inputs, and K^{ST} is structures. γ_t are year-specific intercepts. The error terms consists of an unobserved industry-specific effect, η, and a disturbance term $\nu_{i,t}$ that accounts for various disturbances like measurement error or true productivity shocks that could be autoregressive. Constant returns are not imposed.

Equation (11) can be estimated in various ways, depending on how one views the composite error term and addresses potential simultaneity and omitted variable problems.[31] If there are no

[30] McGuckin and Stiroh (2000b) compare the Blundell and Bond (1998a) approach to OLS and fixed effects estimates in value-added production function estimates.
[31] See Griliches and Mairesse (1998) for a comprehensive review of this problem.

industry-specific effects and all shocks were revealed after input decisions were made, these problems are not present and OLS is appropriate. Alternatively, if industry-specific effects are present and productivity shocks are uncorrelated with all inputs in all periods (strict exogeneity), then a standard fixed effects or first difference estimate is appropriate to remove industry-specific effects. Finally, if industry-specific effects are present and shocks are correlated with inputs, then one can estimate Equation (11) in first differences to remove fixed effects and use appropriate instruments to account for the simultaneity problem as in Arellano and Bond (1991).

The appropriate set of instruments for this type of estimation has been a subject of much discussion. Building on the work of Arellano and Bond (1991), Arellano and Bover (1995), and others, Blundell and Bond (1998a, 1998b) present a GMM estimator that provides efficiency gains relative to a basic first difference estimator. They propose a system-GMM (SYS-GMM) estimator based on a stacked system of equations in first differences (with lagged levels, dated *t-2* and earlier, as instruments) and equations in levels (with lagged first differences, dated *t-1*, as instruments).

Blundell and Bond (1998b) also emphasize the importance of allowing for an autoregressive component in the productivity shocks. If one believes the autoregressive component is not present, then Equation (11) can be estimated directly using their SYS-GMM estimator. If errors are autoregressive, however, then lagged independent variables will not be valid instruments. In this case, Equation (11) must be transformed to a dynamic (common factor) representation with serially uncorrelated errors by including lags of the dependent variable and all independent variables as regressors. The common factor restriction can be imposed and tested.[32]

Table 7 presents three sets of estimates of Equation (11). The first set reports ordinary least squares (OLS) estimates from regressions in levels. The second set reports SYS-GMM estimates from the stacked system of levels and first differences (Static GMM-SYS), under the assumption of no serial correlation in errors. The third set reports SYS-GMM estimates from the dynamic model (Dynamic SYS-GMM), which is appropriate if $v_{i,t}$ contains a first-order autoregressive component. The common factor restrictions are imposed. All SYS-GMM estimates treat intermediate inputs, labor, and capital as potentially endogenous variables with lagged levels dated t-2 as instruments in the first difference equation and lagged first differences dated t-1 as instruments in the levels equation. For each estimator, Table 7 presents a general production function in Equation (11) and a more

[32]The common factor restriction imposes that the coefficient on the lagged independent variables equals the negative of the product of the coefficient on the lagged dependent variable and the current independent variable, where the coefficient on the lagged dependent variable is the estimate of the autoregressive coefficient. See Blundell et al. (1992) and Blundell and Bond (1998b) for details.

restricted form that includes only a single, aggregate measure of capital input. In all cases, estimates are for the 49 industries from 1977 to 1996 in order to maximize the time series dimension.[33]

The results are largely reasonable and indicate a significant role for IT. In the OLS and Static GMM-SYS estimates, intermediate input and labor coefficients are close to their input share as predicted by the standard neoclassical production function with constant returns. Aggregate capital is insignificant and small, although the breakdown of capital into IT, other equipment, and structures shows a significant coefficient on IT and structures separately. Given the small size of the IT capital stock, this coefficient appears relatively large and implies that IT is quite productive. Note, however, that this does not necessarily imply excess returns to IT. Since IT has high user costs, it must also have high marginal products for compensation. As in the earlier regressions, other equipment appears to have a negative impact on output. Finally, there appears to be slightly decreasing returns to scale of about 0.9-0.95, which is consistent with Basu and Fernald (1997).

The OLS estimates should not be taken too seriously, however, due to the omitted variables and simultaneity problems in this type of estimation. In terms of the Static SYS-GMM estimators, if the disturbances $v_{i,t}$ are not serially correlated as assumed for estimation, then first differenced residuals should show significant negative first-order serial correlation and no evidence of second-order serial correlation. The data, however, do not reject the null of no first-order serial correlation in the first differenced residuals, which suggests that the dynamic model is a more appropriate specification.

The results from the Dynamic SYS-GMM estimator are somewhat more mixed, however. Aggregate capital is now statistically significant and a more reasonable size, and the capital breakdown again shows a significant impact from IT capital and structures. The tests of serial correlation reject the null of no first-order serial correlation in the first differenced residuals and fail to reject the null of no second-order serial correlation, as required. However, the labor coefficient increases above expectations and the intermediate input coefficient drops substantially. Returns to scale drops to the 0.8 range. The common factor restriction is not rejected when capital is decomposed, suggesting the last column is the most appropriate specification.

These production function estimates are largely reasonable and show an important role for IT capital as a source of productivity. This is again consistent with the earlier results that found IT-intensive industries experienced relatively large productivity gains and that IT investment leads productivity growth. Taken together, these results provide strong econometric evidence that IT capital

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[33]Estimation is done with the DPD98 Gauss program described by Arellano and Bond (1998).

is indeed quite productive and complements the aggregate studies that attribute an important role for IT capital in the U.S. productivity revival.

V. Industry Decomposition of Labor Productivity

The previous results show a strong link between IT and productivity for individual U.S. industries. Since much of the discussion of the U.S. productivity revival focuses on aggregate data, one would also like to be able quantify the contribution from IT-related industries to the aggregate estimates. With this goal in mind, I present a relatively straightforward decomposition that allows a better understanding of the industry sources of aggregate labor productivity growth.

Domar (1961) developed a means for disaggregating aggregate total factor productivity growth into industry contributions. This “Domar-weighting” methodology was extended by Jorgenson, Gollop, and Fraumeni (1987) and Basu and Fernald (1997a, 1999) and recently implemented by Gullickson and Harper (1999) and Jorgenson and Stiroh (2000a, 2000b). Those papers focused on decomposing total factor productivity growth to identify and isolate the sources of technological progress; I present a similar decomposition for labor productivity.

This is a useful exercise since it identifies where aggregate labor productivity gains are originating, and also provides a clear link between the industry-level gross output productivity estimates and the aggregate value-added data. Moreover, there are considerable lags in total factor productivity data, which is typically available only for aggregates and certain parts of the economy, while labor productivity data are available more quickly and at a detailed level for the entire economy. Thus, this approach allows a more timely assessment of the industry sources of labor productivity growth.

a. Labor Productivity Decomposition

At the aggregate level, labor productivity is typically defined using a value-added concept, say GDP or nonfarm business output, as:

$$(12) \qquad ALP^V = V / H$$

where V is aggregate real value-added and H is aggregate hours worked.

Consistent with the chain-weighted approach currently used in the BEA data, aggregate value-added can be expressed as an index of value-added growth for the component industries. For simplicity, use a Tornqvist index and define aggregate output growth as:

$$(13) \qquad d \ln V = \sum_i \overline{w}_i d \ln V_i$$

where $\overline{w}_i$ is a two-period average of nominal value-added shares and V_i is industry i real value-added.[34]

Aggregate labor input is the simple sum of industry labor, H_i:

$$(14) \qquad H = \sum_i H_i$$

The BEA currently uses the "double deflation" method for all industries where estimates of real gross output and real intermediate inputs are used to define real value-added (GPO).[35] An alternative advocated by Arrow (1974) and Basu and Fernald (1995, 1997a) defines real-value added growth implicitly as:

$$(15) \qquad d\ln Y_i = (1 - s_M)d\ln V_i + s_M d\ln M_i$$

where s_M is the intermediate input share of nominal output.[36]

Rewriting Equations (4) and (12) in growth rates and combining with Equations (13) and (15) yields the following decomposition of aggregate labor productivity growth:

$$(16) \qquad \begin{aligned} d\ln ALP^V &= \left(\sum_i \overline{w}_i d\ln ALP_i^Y\right) - \left(\sum_i \overline{m}_i \left(d\ln M_i - d\ln Y_i\right)\right) + \left(\sum_i \overline{w}_i d\ln H_i - d\ln H\right) \\ &= \left(\sum_i \overline{w}_i d\ln ALP_i^Y\right) - R^M + R^H \end{aligned}$$

which simplifies to:

$$(17) \qquad \begin{aligned} d\ln ALP^V &= \left(\sum_i \overline{w}_i d\ln ALP_i^V\right) + \left(\sum_i \overline{w}_i d\ln H_i - d\ln H\right) \\ &= \left(\sum_i \overline{w}_i d\ln ALP_i^V\right) + R^H \end{aligned}$$

where $\overline{w}_i$ is the two-period average share of industry value-added in aggregate value-added and $\overline{m}_i$ is the two-period average ratio of the industry intermediate inputs to aggregate value-added, in nominal terms.

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[34]In practice, BEA uses a Fisher Ideal Index of industry real value-added to construct their measure of gross product originating for Private Industries. The Tornqvist index is a superlative index for flexible functional forms like the translog and provides a close approximation to the Fisher Ideal. A problem occurs, however, when one would like to include series that change signs, like the statistical discrepancy.

[35]See Yuskavage (1996) and Lum et al. (2000) for details.

[36]This definition differs from the double deflation method used by BEA since that essentially uses base-year prices in the weights, while the Tornqvist index uses current-period prices. This introduces very small approximation errors when compared to the double-deflated estimates of BEA. See Basu and Fernald (1995) for details.

Equation (16) decomposes aggregate value-added labor productivity growth into a direct contribution of industry gross output productivity growth and two reallocation terms, while Equation (17) presents the decomposition in terms of industry value-added productivity growth and one reallocation term. Each is discussed in turn.

The first term in Equation (16) is a direct productivity effect equal to the weighted average of labor productivity in component industries, where productivity is defined using the preferred gross output concept and weights are average value-added shares. As industries improve their productivity, aggregate productivity rises in proportion with industry size. This term reflects the direct contribution of industry productivity growth and corresponds to a "within effect" in a traditional shift/share analysis. The second term, R^M, is a reallocation of materials that reflects variation in intermediate input intensity across industries and enters with a negative sign. If industries are using more intermediate inputs to raise gross output, $(d\ln M_i > d\ln Y_i)$, then this must be netted out to reach aggregate productivity.[37] The third term, R^H, is a reallocation of hours. Aggregate hours growth, $d\ln H$, approximately weights industries by their (lagged) share of aggregate hours, so aggregate productivity rises if industries with value-added shares above labor share experience hours growth. This reallocation effect is a real economic force as the economy move resources among industries with different productivity levels.

Equation (17) simplifies the decomposition and reduces the first two terms to the industry value-added productivity concept. Here, aggregate productivity growth reflects the direct contribution from industry value-added productivity growth, with weights again equal to value-added shares, plus the reallocation of hours worked to high productivity industries. Note, however, that this simplification introduces the value-added productivity concept, which is a less meaningful productivity concept.[38]

b. Decomposition Estimates

This section reports the labor productivity decomposition in Equations (16) and (17) and allocates aggregate labor productivity growth across industries. The direct contributions are broken down across three types of industries – IT-producing, IT-using, and all others – in order to determine the impact of each part of the economy on aggregate productivity growth.

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[37]This is similar to the intermediate intensity term in Basu and Fernald (1997b, Equation 17).

[38]Nordhaus (2000) presents a similar decomposition, where aggregate productivity reflects a "pure productivity effect" (impact of productivity growth in each industry), a "Baumol effect" (impact of difference between current and base-year weights), and a "Denison effect" (impact of changing shares and relative productivity levels). Nordhaus' pure productivity effect is analogous to the first term in Equation 16, while his Denison effect corresponds to the reallocation effect.

The IT-producing industries are the two manufacturing industries, industrial machinery and equipment (SIC #35) and electronic and other electric equipment (SIC #36), that produce computer hardware, semi-conductors, telecommunications equipment, and other high-tech gear. The 26 IT-using industries have an above-median value for the preferred IT-intensity indicator, the 1995 nominal IT share of capital services. The remaining 33 industries are included in the all other category, which also includes the four service industries for which capital stock data are not available.

Table 8 reports results. The first row reports aggregate productivity growth for the private economy, excluding the statistical discrepancy. For each period, the first column reports the value-added weights ($\sum_i \overline{w}_i$) and the second column reports the net contribution to aggregate productivity ($\sum_i \overline{w}_i d \ln ALP_i^Y$ or $\sum_i \overline{w}_i d \ln ALP_i^V$) for all industries and the subsets of 2 IT-producing industries, 26 IT-using industries, and 33 other industries. The reallocation effects, R^M and R^H, are summed over all industries. The last column reports the change in contribution between 1987-95 and 1995-99. For example, aggregate value-added productivity increased by 1.36 percentage points, with 0.90 percentage point from the direct contribution of faster gross output productivity growth in individual industries, 0.29 due to a change in reallocation of materials, and 0.15 due to a change in reallocation of labor.

As expected, the majority of aggregate productivity growth reflects the direct contribution of faster industry productivity growth. The breakdown across industries, however, shows that productivity gains were highly concentrated in IT-related industries. For 1995-99, for example, the relatively small IT-producing industries (4% share) contributed 0.53 percentage point, the large IT-using industries (66% share) contributed 1.77 percentage points, and the large set of other industries (30% share) contributed only 0.47 percentage point. The relatively large contributions from IT-related industries reflects their large productivity growth rates in the late 1990s, e.g., mean annual growth rates of 12.2% per year for the two IT-producing industries, 2.7% for the 26 IT-using industries, and 2.2% for the 31 other industries. These IT-related industries are also capturing a larger share of aggregate inputs, e.g., mean labor growth was 0.6% per year for IT-producing industries, 2.9% for IT-using industries, and only 0.1% for the other industries. This is reasonable, as one would expect more productive industries to expand.

It is interesting to note that the material and labor reallocation terms are negative in both periods. The negative material reallocation means material input growth is outpacing gross output growth on average, which must be netted out from the direct industry contributions since it reflects inter-industry trade that does not increases in aggregate value-added. In terms of labor reallocation, the negative effect primarily reflects several non-IT-intensive industries with strong labor growth, but value-added shares below labor shares, e.g., construction, social services, and educational services. Nordhaus (2000) also reports a negative labor reallocation term (his Denison effect).[39]

The comparison of the three sets of industries is even more dramatic when one examines the U.S. productivity revival by focusing on changes between 1987-95 and 1995-99. The two IT-producing industries are responsible for about one-fifth of the productivity acceleration attributed to gains in specific industries.[40] The IT-using industries account for almost all of the remainder, 0.66 percentage point, while the remaining industries made a direct contribution from their own productivity gains of only 0.07. Note that the reallocation effects have been declining in size, which is consistent with more open markets and less regulation that allow more efficient resource reallocations.

The bottom panel of Table 8 consolidates the resource reallocation effects with gross output productivity and looks at value-added productivity growth contributions for the three groups of industries as in Equation 17. Here, the two sets of IT-related industries account for more than the entire productivity acceleration, while the other industries that are relatively isolated from IT made essentially no contribution to productivity growth for 1995-99 and a *negative* 0.27 percentage point contribution on net to the aggregate productivity acceleration.

This decomposition framework shows that the role of IT-related industries in U.S. productivity growth is quantitatively large and economically important at a macro level. Virtually all of the industry-specific productivity gains are originating in the industries that either produce or use IT most intensively, while other industries have made little contribution on net. While one can debate the direction of causation, these results clearly show that IT-related industries are driving the U.S. productivity revival and that other industries are playing a inconsequential role.

VI. Conclusions

The U.S. economy has experienced a sharp acceleration of productivity growth in recent years and IT-related forces have emerged as an appealing candidate to explain those gains. The results in this paper strengthen that view by establishing a strong link between IT capital accumulation and productivity growth across U.S. industries. In particular, those industries that made the largest IT investments in the early 1990s show larger productivity gains in the late 1990s and production

[39]One may be tempted to infer if value-added shares exceed labor shares, then the industry has relatively high productivity levels. This is not necessarily true, however, since value-added shares are calculated in nominal values, while productivity depends on real output.
[40]The weights for the three industry groups are relatively constant over the two periods. While the IT-producing industries have been growing rapidly in real terms, the prices of these goods have been falling, so that the nominal shares are essentially unchanged.

function estimates show a relatively large elasticity of IT capital, indicating that IT capital accumulation is important for business output and productivity.

A decomposition of aggregate productivity growth into the contribution of individual industries and inter-industry reallocation effects shows IT-related differences to be large and important for understanding the U.S. productivity revival. IT-producing and IT-using industries account for virtually all of the productivity revival that is attributable to the direct contributions from specific industries, while industries that are relatively isolated from the IT revolution essentially made no contribution to the U.S. productivity revival. Thus, the U.S. productivity revival seems to be fundamentally linked to IT.

This evidence also supports the idea that the acceleration of aggregate productivity is a real phenomenon and not only a cyclical one. Given the substantial differences in productivity growth between IT-intensive and other industries, cyclical forces would have to be highly concentrated in precisely those industries that are most IT-intensive for this to be the whole story. The strong and robust correlation between IT-intensity and productivity acceleration, however, implies that there is a deeper relationship between IT investment and productivity growth.

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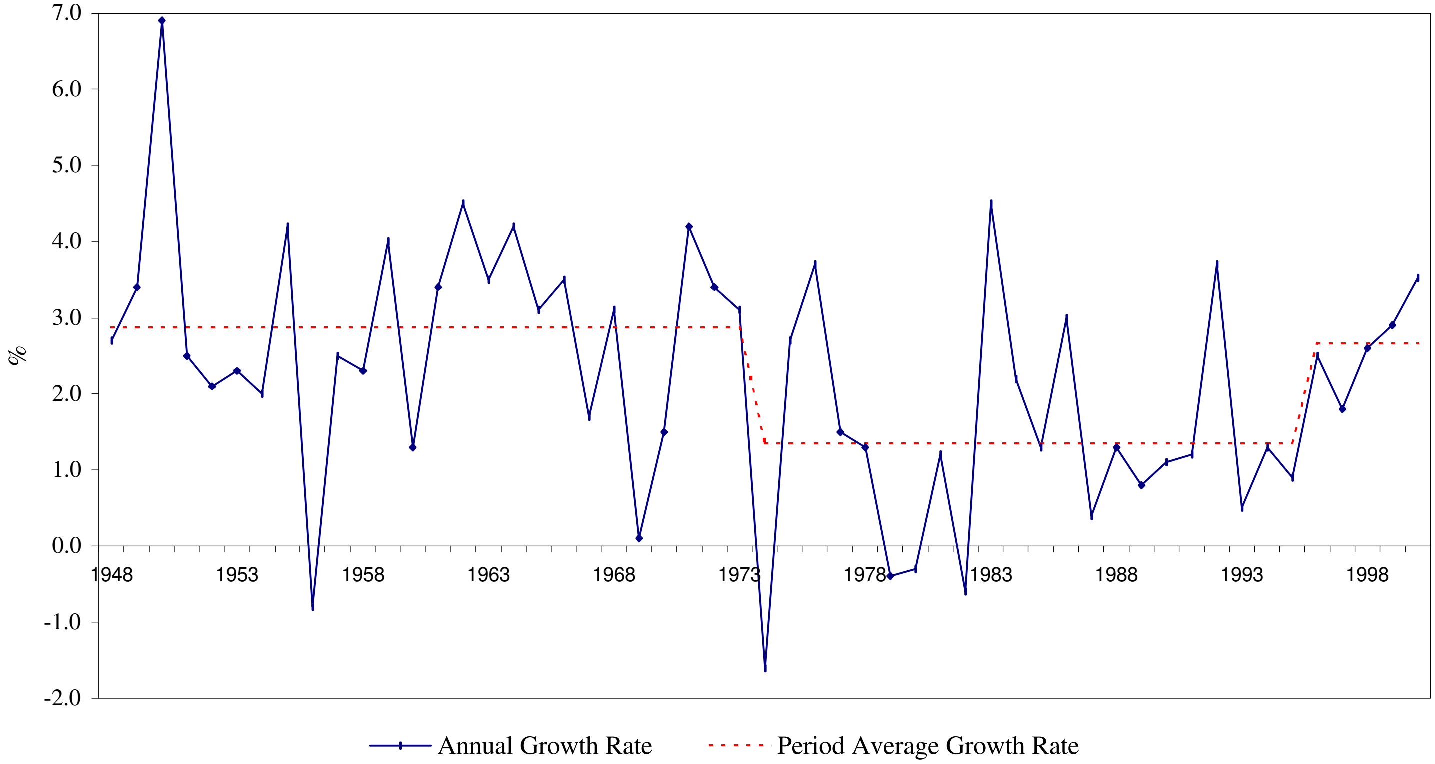
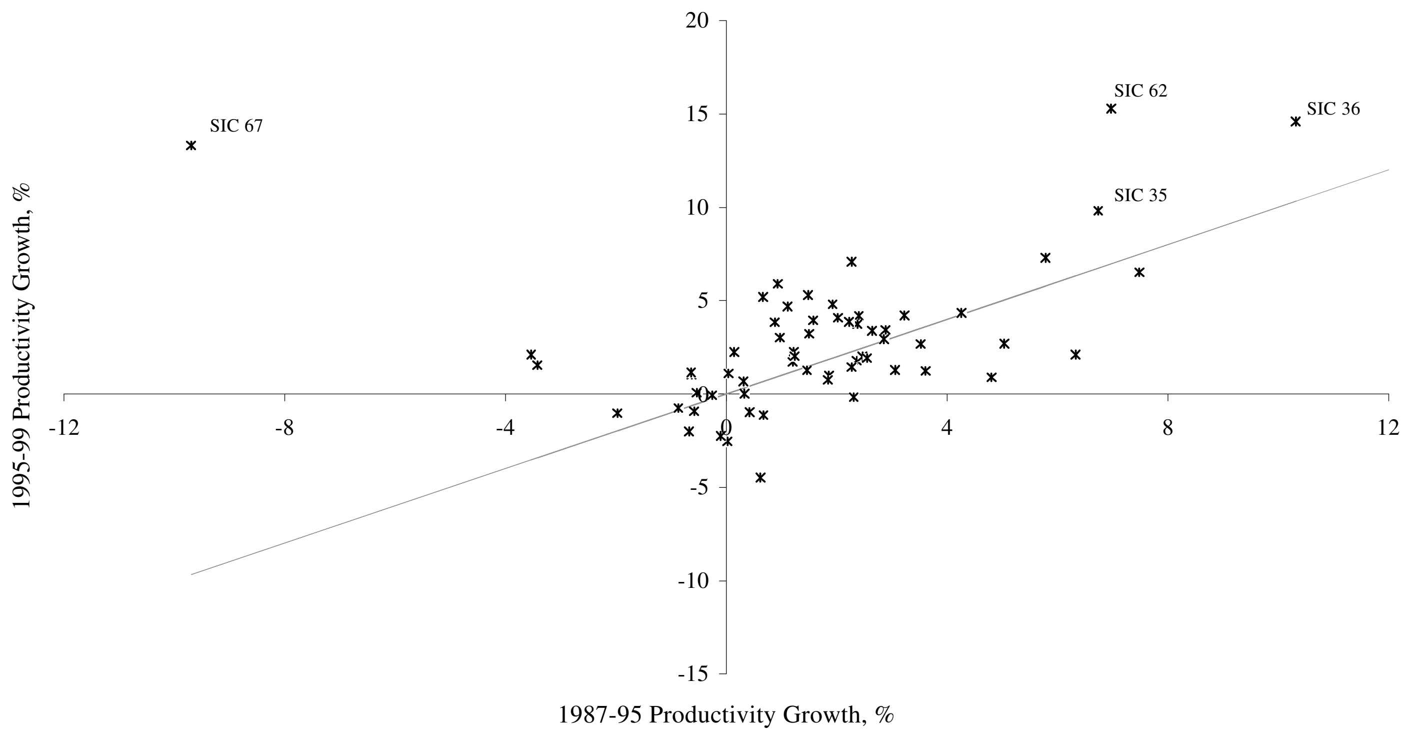
Chart 1: U.S. Productivity Growth, 1947-2000



Source: BLS (2000b). Estimates are annual growth rates for the nonfarm business sector, except 2000 which is through three quarters. The average growth rates are for 1947-73, 1973-95, 1995-2000:Q3.

Chart 2: Changes in Industry Productivity Growth

1987-95 vs. 1995-99



Notes: All productivity growth refers to annualized growth in real gross output per FTE. Outlier industries include: SIC #35, industrial machinery and equipment; SIC #36, electronic and other electric equipment; SIC #62 security and commodity brokers; SIC #67, holding and other investment offices.

Table 1: Alternative Explanations of the U.S. Productivity Revival

	BLS	Gordon	Jorgenson & Stiroh	Oliner & Sichel
ALP Revival Period, 1995-99	2.30	2.75	2.37	2.57
ALP Early Period, 1973-95	1.39	1.42	1.42	1.41
Acceleration	0.91	1.33	0.95	1.16
Capital Deepening	0.10	0.33	0.29	0.33
IT-Related	0.38	-na-	0.34	0.50
Other	-0.31	-na-	-0.05	-0.17
Labor Quality	0.06	0.05	0.01	0.04
TFP	0.90	0.31	0.65	0.80
IT-Related	-na-	0.29	0.24	0.31
Other	-na-	0.02	0.41	0.49
Cyclical Effect		0.50		
Price Measurement		0.14		

Notes: Revival period is 1995-98 for Jorgenson and Stiroh. BLS, Oliner and Sichel, and Gordon examine nonfarm business sector; Jorgenson and Stiroh include business sector plus private households. Gordon compares the revival period to trend productivity growth for the early period. IT-related capital deepening refers to information processing equipment and software for BLS, and computer hardware, software and telecommunications equipment for Jorgenson and Stiroh and Oliner and Sichel. IT-related TFP is from computer plus computer-related semiconductors for Gordon and Oliner and Sichel and from computer harder, software, and telecommunications for Jorgenson and Stiroh. Numbers may not add up due to rounding.

Source: BLS (2000b), Gordon (2000), Jorgenson and Stiroh (2000), Oliner and Sichel (2000).

Table 2: Average Productivity Growth Rates, 1977-99

	Annual Growth Rate (%)			Acceleration	
				1995-99 less	1995-99 less
	1977-95	1987-95	1995-99	1977-95	1987-95
			Value-Added - Aggregate Measures		
Gross domestic product	1.04	1.05	1.69	0.65	0.64
Private industries (BEA)	0.92	1.03	2.01	1.09	0.97
Private industries (Sector Aggregate)	0.97	0.98	2.34	1.37	1.36
			Gross Output - Aggregate Measures		
Private industries	-na-	1.23	2.38	-na-	1.15
			Gross Output - Broad Sectors		
Agriculture, forestry, and fishing	1.38	0.58	-0.67	-2.05	-1.25
Mining	2.28	3.14	2.50	0.22	-0.64
Construction	-1.23	-0.87	-0.76	0.47	0.11
Durable goods manufacturing	3.14	3.97	6.47	3.33	2.50
Nondurable goods manufacturing	1.64	1.48	3.31	1.67	1.84
Transportation and public utilities	-na-	2.27	2.38	-na-	0.11
Wholesale trade	2.14	3.23	4.22	2.07	0.98
Retail trade	0.42	0.97	3.03	2.60	2.06
Finance, insurance, and real estate	-na-	2.33	2.88	-na-	0.54
Services	-na-	0.39	1.24	-na-	0.85
			Gross Output - Industry Averages		
Mean - 61 Industries	-na-	1.68	2.77	-na-	1.09
Median - 61 Industries	-na-	1.50	2.10	-na-	0.60
Mean - 49 Industries	1.61	1.80	2.80	1.19	0.99
Median - 49 Industries	1.45	1.48	2.04	0.99	0.80

Notes: Productivity estimates use either real value-added or real gross output per full-time equivalent employees (FTE). Private industries (BEA) includes statistical discrepancy; Private industries (Sector Aggregate) does not. Number of detailed industries varies with the available data for the period and output measure. Industry mean and medians are for period averages.

Table 3: Dummy Variable Tests of Acceleration of Industry Productivity Growth

			1987-99		
Constant	1.678***	1.365**	1.067***	1.062**	1.016**
	(0.394)	(0.497)	(0.324)	(0.325)	(0.344)
Post-1995 Dummy	1.092	0.987**	0.908**	0.798*	0.725*
	(0.678)	(0.373)	(0.348)	(0.355)	(0.375)
Weights		yes	yes	yes	yes
Drop IT-Producing Industries			yes	yes	yes
Drop FIRE Outliers				yes	yes
Drop Durable Goods Mfg					yes
Number of Obs.	732	732	708	684	576
Number of Industries	61	61	59	57	48
			1977-99		
Constant	1.605***	1.139*	0.784*	0.754*	0.675
	(0.414)	(0.557)	(0.383)	(0.385)	(0.415)
Post-1995 Dummy	1.193**	1.294**	1.152**	1.069*	1.000
	(0.469)	(0.510)	(0.499)	(0.509)	(0.559)
Weights		yes	yes	yes	yes
Drop IT-Producing Industries			yes	yes	yes
Drop FIRE Outliers				yes	yes
Drop Durable Goods Mfg					yes
Number of Obs.	1,078	1,078	1,034	1,012	836
Number of Industries	49	49	47	46	38

Notes: Dependent variable is productivity growth for industry i in year t. Post-1995 dummy equals 1 if t>1995, 0 otherwise. Weights represent weighted least squares using FTE as the weight. Standard errors in parentheses. All estimates allow errors to be correlated for industries within the same sector and are corrected for heteroskedasticity. IT-producing industries are Industrial Machinery and Equipment (SIC #35) and Electronic and Other Electric Equipment (SIC #36). FIRE outliers are Security and Commodity Brokers (SIC #62) and Holding and other Investment Offices (SIC #67). Durable goods manufacturing includes SIC #24, 25, 32-39.

Table 4: Dummy Variable Tests of Productivity Acceleration for IT-Intensive Industries

	Alternative Indicators of IT-Intensity				IT Share of Capital		
	IT Share of Capital	IT Share of Output	IT Capital per FTE	Composite			
Constant	1.177*	0.724	0.691*	0.629	1.177*	1.177*	1.177*
	(0.574)	(0.490)	(0.321)	(0.487)	(0.574)	(0.574)	(0.574)
IT-Intensive Dummy	0.434	1.249	2.017**	1.391	-0.024	0.434	-0.030
	(0.847)	(0.780)	(0.770)	(0.774)	(0.648)	(0.853)	(0.649)
Post-95 Dummy	0.120	0.444	0.890	0.290	0.120	0.120	0.120
	(0.665)	(0.521)	(0.580)	(0.436)	(0.666)	(0.666)	(0.666)
Post-95 Dummy*IT-Intensive Dummy	1.371**	1.073	0.532	1.310**	1.282*	1.216*	1.116
	(0.578)	(0.616)	(0.584)	(0.425)	(0.656)	(0.628)	(0.718)
Drop IT-Producing Industries					yes		yes
Drop FIRE Outliers						yes	yes
Number of Obs.	684	684	684	684	660	660	636
Number of Industries	57	57	57	57	55	55	53

Notes: Dependent variable is productivity growth for industry *i* for 1987 to 1999. Post-1995 dummy equals 1 if t>1995, 0 otherwise. IT-intensive dummy equals 1 for industries with a 1995 value above the 1995 median, 0 otherwise. Composite index dummy equals 1 if two of the three indicators equals 1, 0 otherwise. All estimates are weighted least squares using FTE as the weights. Standard errors in parentheses. All estimates allow errors to be correlated for industries within the same sector and are corrected for heteroskedasticity. IT-producing industries are Industrial Machinery and Equipment (SIC #35) and Electronic and Other Electric Equipment (SIC #36). FIRE outliers are Security and Commodity Brokers (SIC #62) and Holding and other Investment Offices (SIC #67).

Table 5: Impact of Continuous Measures of IT-Intensity on Productivity Acceleration

	Alternative Indicators of IT-Intensity					
	IT Share of Capital	IT Share of Output	IT Capital per FTE	IT Share of Capital		
Constant	1.480**	1.480**	1.480**	1.161***	1.479**	1.157***
	(0.481)	(0.481)	(0.481)	(0.303)	(0.485)	(0.305)
Post-1995 Dummy	0.924	1.181**	1.230**	0.828	0.834	0.734
	(0.513)	(0.403)	(0.370)	(0.508)	(0.520)	(0.514)
Post-1995 Dummy * IT-Intensity	0.804***	0.993*	0.792**	0.836***	0.723***	0.753***
	(0.207)	(0.494)	(0.316)	(0.200)	(0.201)	(0.209)
Drop IT-Producing Industries				yes		yes
Drop FIRE Outliers					yes	yes
Number of Obs.	684	684	684	660	660	636
Number of Industries	57	57	57	55	55	53

Notes: Dependent variable is productivity growth for industry *i* for 1987- to 1999. Post-1995 dummy equals 1 if t>1995, 0 otherwise. IT-intensity enters the regression as the normalized value of the IT variable defined in text. All estimates are weighted least squares using FTE as the weights. All estimates allow errors to be correlated for industries within the same sector and are corrected for heteroskedasticity. IT-producing industries are Industrial Machinery and Equipment (SIC #35) and Electronic and Other Electric Equipment (SIC #36). FIRE outliers are Security and Commodity Brokers (SIC #62) and Holding and other Investment Offices (SIC #67).

Table 6: Impact of Lagged Input Accumulation on Recent Productivity Growth

	Period for Lagged Dependent Variables					
	1992-95		**1990-95**		**1987-95**	
Lagged Productivity Growth	0.888***	0.601***	0.908***	0.722***	1.071**	0.999***
	(0.077)	(0.172)	(0.096)	(0.107)	(0.419)	(0.151)
Lagged Growth of Intermediate Input / FTE	-0.085	-0.018	0.120**	0.077	-0.066	-0.220**
	(0.050)	(0.051)	(0.037)	(0.060)	(0.271)	(0.086)
Lagged Growth of Other Equipment / FTE	-0.161	-0.132	-0.309***	-0.267***	-0.350*	-0.332***
	(0.135)	(0.101)	(0.101)	(0.070)	(0.175)	(0.095)
Lagged Growth of Structures / FTE	0.155	-0.122	0.021	0.019	0.086	0.009
	(0.101)	(0.116)	(0.117)	(0.111)	(0.171)	(0.157)
Lagged Growth of IT / FTE	0.088***	0.091***	0.157***	0.178***	0.133	0.222***
	(0.013)	(0.023)	(0.027)	(0.028)	(0.089)	(0.051)
Constant	0.518**	0.491	-0.707**	-0.719**	-0.110	-0.674
	(0.198)	(0.297)	(0.285)	(0.247)	(0.809)	(0.507)
Drop IT-Producing Industries		yes		yes		yes
Drop FIRE Outliers		yes		yes		yes
Number of Obs.	57	53	57	53	57	53

Notes: Dependent variable is average, annual productivity growth for industry i for 1995-99. Dependent variables are average annual growth rates for lagged variables for periods indicated by the columns. All estimates are weighted least squares using FTE as the weights. Standard errors in parenthesees. All estimates allow errors to be correlated for industries within the same sector and are corrected for heteroskedasticity. IT-producing industries are Industrial Machinery and Equipment (SIC #35) and Electronic and Other Electric Equipment (SIC #36). FIRE outliers are Security and Commodity Brokers (SIC #62) and Holding and other Investment Offices (SIC #67)

Table 7: Production Function Estimates, 1977-96

	OLS		Static GMM-SYS		Dynamic GMM-SYS	
M_t	0.643***	0.713***	0.445***	0.611***	0.163***	0.202***
	(0.051)	(0.048)	(0.150)	(0.076)	(0.031)	(0.031)
L_t	0.250***	0.208***	0.395***	0.225***	0.417***	0.408***
	(0.049)	(0.045)	(0.101)	(0.048)	(0.044)	(0.027)
K_t	0.052		0.062		0.131*	
	(0.042)		(0.074)		(0.073)	
$K_{IT,t}$		0.051***		0.086***		0.045**
		(0.016)		(0.025)		(0.015)
$K_{EQ,t}$		-0.086**		-0.059		-0.019
		(0.033)		(0.045)		(0.060)
$K_{ST,t}$		0.074**		0.083*		0.137***
		(0.035)		(0.044)		(0.035)
Y_{t-1}					0.973***	0.975***
					(0.011)	(0.014)
SC-1			0.24	0.22	0.00	0.00
SC-2			0.08	0.22	0.41	0.38
Sargan Statistics			31.3	32.9	25.3	23.9
(Degrees of Freedom)			(105)	(175)	(101)	(169)
ComFac					0.02	0.192
No. of Observations	980	980	980	980	931	931

Notes: Dependent variable is real gross output. All estimates are for 49 industries for 1977 to 1996 with time dummies. OLS is ordinary least squares regressions in levels. Static SYS-GMM is the GMM system estimator with the following instruments: lagged first differences for the levels equation and lagged levels for the first difference equation. Dynamic SYS-GMM uses the same instruments, but includes the lagged depenedent and independent variables as regressors. The common factor restriction is imposed and tested. Standard errors are asymptotically robust to heteroskedasticity and reported in parentheses. SC-1 and SC-2 are p-values for tests of first-order and second-order serial correlation in the first differenced residuals, against the null of no serial correlation. Sargan Statistics are for the test of overidentifying restrictions, distributed as chi-squared with degress of freedom in parentheses. ComFac is the p-value of the test of common factor restriction.

Table 8: Aggregate Labor Productivity Decomposition, 1987-99

	1987-95		1995-99		Change
Aggregate Productivity Growth	0.98		2.34		1.36
Decomposition using Industry Gross Output Productivity					
	Weight	**Contribution**	**Weight**	**Contribution**	
Weighted ALP^Y	1.000	1.86	1.000	2.76	0.90
IT-Producing	0.044	0.37	0.043	0.53	0.16
IT-Using	0.646	1.10	0.660	1.77	0.66
Other	0.310	0.39	0.297	0.47	0.08
Material Reallocation, $-R^M$		-0.40		-0.12	0.29
Hours Reallocation, R^H		-0.47		-0.32	0.15
Decomposition using Industry Value-Added Productivity					
	Weight	**Contribution**	**Weight**	**Contribution**	
Weighted ALP^V	1.000	1.45	1.000	2.65	1.20
IT-Producing	0.044	0.40	0.043	0.68	0.28
IT-Using	0.646	0.68	0.660	1.86	1.19
Other	0.310	0.37	0.297	0.10	-0.27
Hours Reallocation, R^H		-0.47		-0.32	0.15

Note: Decomposition framework is defined in Equations (16) and (17). Weights are sum of nominal, value-added shares; contribution is sum of share weighted productivity growth. IT-Producing industries include two industries, SIC #35 and #36; IT-Using industries include 26 industries, defined by above median 1995 IT capital share; Other industries include the remaining 33 industries, which includes four industries with no detailed capital data.

Appendix Table A: Industry Breakdown and Relative Size

SIC	Industry	Sector	1996 Gross Output	1996 Capital Stock
01-02	Farms	Agriculture, forestry, and fishing	222.6	315.3
07-09	Agricultural services, forestry, and fishing	""	55.8	51.3
10	Metal mining	Mining	12.6	35.2
12	Coal mining	""	27.1	36.2
13	Oil and gas extraction	""	129.8	344.3
14	Nonmetallic minerals, except fuels	""	17.0	20.8
15-17	Construction	Construction	554.5	88.2
24	Lumber and wood products	Durable Goods Manufacturing	105.6	29.3
25	Furniture and fixtures	""	54.5	13.3
32	Stone, clay, and glass products	""	80.6	43.4
33	Primary metal industries	""	178.7	127.8
34	Fabricated metal products	""	210.0	81.9
35	Industrial machinery and equipment	""	371.2	128.6
36	Electronic and other electric equipment	""	313.8	128.8
371	Motor vehicles and equipment	""	326.1	86.0
372-379	Other transportation equipment	""	136.2	53.4
38	Instruments and related products	""	147.9	53.0
39	Miscellaneous manufacturing industries	""	49.1	14.0
20	Food and kindred products	Nondurable Goods Manufacturing	450.7	145.9
21	Tobacco products	""	39.6	9.2
22	Textile mill products	""	79.6	37.7
23	Apparel and other textile products	""	75.0	13.3
26	Paper and allied products	""	159.3	98.5
27	Printing and publishing	""	197.3	60.0
28	Chemicals and allied products	""	358.6	206.4
29	Petroleum and coal products	""	170.6	92.6
30	Rubber and miscellaneous plastics products	""	147.8	54.7
31	Leather and leather products	""	9.0	2.6
40	Railroad transportation	Transportation and Public Utilities	40.7	360.6
41	Local and interurban passenger transit	""	24.2	19.9
42	Trucking and warehousing	""	213.8	108.2
44	Water transportation	""	36.4	36.0
45	Transportation by air	""	117.3	110.1
46	Pipelines, except natural gas	""	7.8	48.3
47	Transportation services	""	37.7	42.7
481,482, 489	Telephone and telegraph	""	270.0	468.4
483-484	Radio and television	""	78.8	93.7
49	Electric, gas, and sanitary services	""	336.2	1,014.3
50-51	Wholesale trade	Wholesale Trade	789.8	402.7
52-59	Retail trade	Retail Trade	1070.9	540.8
60	Depository institutions	Finance, Insurance, Real Estate	342.7	370.3
61	Nondepository institutions	""	108.4	118.1
62	Security and commodity brokers	""	169.3	11.5
63	Insurance carriers	""	261.5	180.2
64	Insurance agents, brokers, and service	""	74.0	6.4
65	Real estate	""	1268.2	1,239.7
67	Holding and other investment offices	""	23.1	33.6
70	Hotels and other lodging places	Services	106.5	127.1
72	Personal services	""	84.6	26.3
73	Business services	""	510.6	126.4
75	Auto repair, services, and parking	""	124.3	114.5
76	Miscellaneous repair services	""	46.4	12.0
78	Motion pictures	""	56.8	29.4
79	Amusement and recreation services	""	110.7	48.5
80	Health services	""	688.0	153.9
81	Legal services	""	134.1	18.9
82	Educational services	""	103.8	18.2
83	Social services	""	98.7	na
86	Membership organizations	""	96.2	na
84,87,89	Other services	""	346.6	na
88	Private households	""	12.0	na
	Private Sum		12,470.5	8,252.5

Note: Gross output and capital stock are measured in billions of current dollars. $79.7B of capital stock is not allocated across industries since detailed data is not available for four detailed industries, indicated by an "na."
Source: Gross output data is from Lum and Moyer (2000); capital stock data is from BEA (1998).

Appendix Table B: Types of Tangible Capital

Asset Type	Asset Class	1996 Capital Stock
Mainframe computers	Information Technology	16.9
Personal computers	""	68.5
Direct access storage devices	""	0.1
Computer printers	""	27.9
Computer terminals	""	23.3
Computer tape drives	""	0.1
Computer storage devices	""	17.2
Other office equipment	Other Equipment	21.8
Communication equipment	Information Technology	391.5
Instruments	Other Equipment	136.2
Photocopy and related equipment	""	82.0
Nuclear fuel rods	""	5.3
Other fabricated metal products	""	90.4
Steam engines	""	53.5
Internal combustion engines	""	6.3
Metalworking machinery	""	205.8
Special industry machinery, n.e.c.	""	240.0
General industrial, including materials handling, equipment	""	220.8
Electrical transmission, distribution, and industrial apparatus	""	261.6
Trucks, buses, and truck trailers	""	259.6
Autos	""	138.0
Aircraft	""	140.3
Ships and boats	""	44.4
Railroad equipment	""	78.3
Household furniture	""	10.5
Other furniture	""	175.7
Farm tractors	""	48.2
Construction tractors	""	12.7
Agricultural machinery, except tractors	""	72.2
Construction machinery, except tractors	""	77.1
Mining and oilfield machinery	""	13.3
Service industry machinery	""	76.8
Household appliances	""	5.2
Other electrical equipment, n.e.c.	""	45.7
Other nonresidential equipment	""	102.1
Industrial buildings	Structures	725.9
Office buildings	""	767.1
Mobile structures	""	8.7
Commercial warehouses	""	181.7
Other commercial buildings, n.e.c.	""	665.4
Religious buildings	""	146.2
Educational buildings	""	138.0
Hospital and institutional buildings	""	325.6
Hotels and motels	""	173.3
Amusement and recreational buildings	""	88.7
Other nonfarm buildings	""	65.9
Local transit buildings	""	12.6
Railroad structures	""	214.2
Railroad track replacement	""	97.0
Telecommunications	""	229.9
Electric light and power	""	481.8
Gas	""	170.4
Petroleum pipelines	""	43.2
Farm related buildings and structures	""	206.1
Petroleum and natural gas exploration	""	244.5
Other mining exploration	""	34.1
Other nonfarm structures	""	143.3
Private Sum		8,332.2

Note: Capital stock measured in billions of current dollars for all private industries.
Source: BEA (1998).