Investment-Specific Technical Change in the US (1947–2000): Measurement and Macroeconomic Consequences*

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Abstract

By extrapolating Gordon's (1990) measures of the quality-bias in the official price indexes, we construct quality-adjusted price indexes for 24 types of equipment and software (E&S) from 1947 to 2000 and use them to measure technical change at the aggregate and at the industry level. Technological improvement in E&S accounts for an important fraction of postwar GDP growth and plays a key role in the productivity resurgence of the 1990s. Driving this finding is 4 percent annual growth in the quality of E&S in the postwar period and more than 6 percent annual growth in the 1990s. The acceleration in the 1990s occurred in every industry, consistent with the idea that information technology represents a general purpose technology. Furthermore, we measure for the aggregate economy and different sectors the "technological gap": how much more productive new machines are compared to the average machine. We show that the technological gap explains the dynamics of investment in new technologies and the returns to human capital, consistent with Nelson and Phelps' (1966) conjecture. Since the technological gap continues to increase — it more than doubled in the past 20 years — our evidence supports the view that at least some of the recent increase in productivity growth is sustainable.

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1 Introduction

Technological improvement in equipment and software in the postwar period has been remarkable. In the field of microelectronics the advances have been spectacular, owing mainly to progress in the manufacture of semiconductors. In the semiconductor industry, Moore's Law — which predicts that the number of transistors per integrated circuit doubles every 18 months — seems to suggest that technical progress is an inexorable process. In fact, progress proceeds apace because firms reap productive benefits by investing in the latest technologies.[1] Investment in microelectronics has been especially widespread so that microelectronics are now the key components in all kinds of goods, resulting in improvements in quality that were once unimaginable. Advances in other technologies like miniaturization have been impressive as well. Moreover, experimental technologies, such as fusion, high-temperature superconductors and quantum computing, hold the promise of even more rapid technical change in the future.

The extent to which such rapid technical change is an engine of growth and a source of interesting macroeconomic dynamics is a quantitative question that can be approached using measures of constant-quality price indexes for capital goods.[2] Building on Gordon's (1990) systematic measurement of quality-adjusted prices for different types of producers' durable equipment, Hulten (1992) and Greenwood, Hercowitz, and Krusell (1997) (GHK) measure the contribution of equipment-embodied technical change to aggregate growth using a Solow (1960) vintage model. Because Gordon's data cover the postwar period until 1983, Hulten's analysis is limited to that period, while GHK extend the aggregate constant-quality price index to 1992

[1] Intel and other semiconductor manufacturers are no exception. In the last 20 years Intel alone spent on average more than two billion per year in constant 1996 dollars on plant, equipment, and R&D.

[2] Production function estimation is an alternative approach to measuring technical change. Bakh and Gort (1993), Gort, Bahk and Wall (1993) and Sakellaris and Wilson (2000) focus on estimating the effect of investment-specific technical change while Stiroh (2001) is a recent entry in the voluminous literature pursuing the more traditional approach which ascribes technical change to the residuals from estimation. In addition, Hobijn (2000) suggests an approach based on structural estimation of an Euler equation for investment.

by applying a constant adjustment factor to the National Income and Product Accounts (NIPA) official price index.

We fill this gap by estimating for each type of equipment the rate of quality improvement since 1983. Starting with Gordon's quality-adjusted price indexes for 1947–83, we estimate the quality bias implicit in the NIPA price indexes for that period. Using the NIPA series, we then extrapolate the quality bias from 1984 to 2000. From this we construct constant-quality price indexes for the capital goods that make up equipment and software (E&S). We view this approach as a sensible albeit crude alternative to the preferable approach that would quality-adjust every asset in E&S using hedonic techniques, a monumental effort that Bureau of Economic Analysis (BEA) is implementing piecemeal.

The speed of technical change for each capital good in E&S can be measured as the difference between the growth rate of constant-quality consumption and the growth rate of the good's quality-adjusted price. Excluding computers and software, for which NIPA price series seem preferable to the ones generated by our alternative approach, we conclude that the greatest technical change occurred in communications equipment (9 percent per year), aircraft (8 percent per year), and instruments (6 percent per year). Using these asset-specific constant-quality price indexes we build an aggregate index of investment-specific technical change for the US economy. This index grows at an average annual rate of 4 percent in the postwar period, with a sharp acceleration in the 1980s that leads to an average annual growth rate of more than 6 percent in the 1990s. Most of the acceleration is due to a shift in investment expenditures towards computers, software, and communications equipment.

We also construct measures of investment-specific technical change at the two-digit and finer industry level using BEA's detailed estimates of E&S investment by industry and type of asset, which are based on a variety of source material including the input-output tables. It comes as no surprise that there are big differences in the rate of technical change at the industry level. For example, the growth rates of the 90th and the 10th percentile of the distribution differ by more than 5 percentage points in each year. What is perhaps surprising given the diversity of industries is that the distribution has remained stable in the postwar period. In particular, the rate of growth accelerates in the 1990s by a similar amount in virtually every industry, demonstrating that information technology affects productivity in a general way. This result as well as others we present support the idea that information technology is a "general purpose" technology.

Previous empirical studies using quality-adjusted measures of investment constructed the productive capital stock with economic depreciation rates from BEA or from Bureau of Labor Statistics. Economic depreciation incorporates the effect of productive decay and obsolescence. We remove the obsolescence component from BEA economic depreciation using our estimates of asset-specific quality improvement. Using these corrected depreciation rates and our quality-adjusted investment price indexes, we construct a measure of the aggregate capital stock for E&S that grows at an annual rate of 8.8 percent in the postwar period. This growth rate is 3 percentage points greater than growth rate of the capital stock constructed using the official depreciation rates and price indexes.

With our estimates of the quality-adjusted productive capital stock, we perform a statistical and an equilibrium growth accounting exercise. Regardless of how real GDP is quality-adjusted, improvement in the quality of E&S explains about 20 percent of growth in the US in the postwar period and about 30 percent of growth in the 1990s. During the 1990s, quality improvement outside of high-tech categories is more important than quality improvement inside high-tech categories — a finding that is underappreciated by those who focus on the role of information technology in the growth resurgence. This explains why our results differ somewhat compared to Jorgenson and Stiroh (2000a) and Oliner and Sichel (2000), which take the official statistics more or less at face value. Although each of these studies find that information technology plays a leading role in the resurgence of GDP growth in the 1990s, they also find that a large part of GDP growth is left unexplained. According to our calculations, the growth rate of this residual — called total factor productivity (TFP) — is 0.4 percentage point in the 1990s, about half the size of the figures in Jorgenson and Stiroh and in Oliner and Sichel. This suggests at least part of growth attributed to TFP by those researchers represents the unmeasured quality of capital that our approach identifies. When we embed this growth accounting exercise in a structural equilibrium model along the lines suggested by GHK, we find that 60 percent of labor productivity growth in the postwar period comes from technological advances in E&S.

Since a substantial increase in the quality of E&S was largely responsible for the growth resurgence in the 1990s, it may be reasonable to suspect that such gains are unsustainable. However, our results show that there is a great deal of potential productivity improvement that remains to be done. Based on our calculations, the technological gap between the productivity of the best technology and the productivity of the average practice in the economy was 15 percent in 1975. In 2000, the figure had jumped to 40 percent. The technological gap actually increased by 5 percentage points in the 1990s, despite the boom in capital spending.

According to Nelson and Phelps (1966), the improvement of the average productivity of capital depends on the technological gap between the best and average technology and on "adaptable" labor which defines human capital. We estimate an adoption equation based on this idea using aggregate data and find that it fits very well. The growth rate of the average practice moves nearly one-for-one with the technological gap and is correlated with measures of adaptable labor (such as the shares in the labor force of college graduates and of young workers).

Another implication of the Nelson and Phelps model is that the returns to adaptability increase with the technological gap. We confirm this by showing that the returns to education and the technological gap move in lock-step during the postwar period. In particular, the technological gap stopped growing in the 1970s, the only period in which wage inequality moderated. When the gap increased in the 1980s and 1990s, wage inequality increased as well. This suggests the technological gap may be a key determinant of wage inequality. Perhaps then rising wage inequality is a persistent feature of economies experiencing rapid technological improvement.

The rest of the paper is organized as follows. Section 2 presents a simple theoretical model in which prices are used to measure investment-specific technical change, outlines the econometric methodology we use to construct the constant-quality price indexes, and describes the estimation results. In section 3, we use the estimates to construct measures of technical change at the aggregate, asset, and industry levels. In section 4, we examine the implications of technical change for postwar growth. Section 5 shows that the technological gap has been growing and that it determines the speed of adoption of new technology and the skill premium. In section 6, we consider the robustness of our results to generalizations of our benchmark model. In the final section, we summarize our major findings and relate them to each other.

2 Methodology

2.1 Measuring Investment-Specific Technical Change Using Prices

Quality improvement in investment goods is pervasive, especially in high-tech categories. For example, a new PC may have the same price today as a new PC had five years ago, but if it provides 10 times as much computing power as before, in effect the constant-quality price of the new PC is one-tenth the price of the old PC. The opportunity cost of innovating — whether it is in producing PCs or tractors — is foregone consumption. Intuition therefore suggests that a comparison of constant-quality investment prices with a constant-quality consumption price is an informative measure of technical change. We formalize this idea in a very simple two-sector model in which an investment good and final goods are produced competitively.

Final goods x_t are produced competitively with some constant returns to scale combination of capital and labor. They can be used for consumption or in the production of efficiency-units of investment goods i_t^*, according to the linear technology

$$i_t^* = q_t x_t, \tag{1}$$

where q_t is a Hicks-neutral index of the state of technology used to produce investment goods.[3] The price of investment goods in efficiency units is $p_t^{i^*}$ and the price of constant-quality consumption goods is $p_t^{c^*}$. Competition in the investment goods sector implies

$$p_t^{i^*} i_t^* = p_t^{c^*} x_t. \tag{2}$$

Using equations (1) and (2) we can measure investment-specific technical change using prices as

$$\frac{p_t^{i^*}}{p_t^{c^*}} = \frac{1}{q_t} \Rightarrow \Delta q_t = \Delta p_t^{c^*} - \Delta p_t^{i^*}, \tag{3}$$

where Δ denotes the growth rate.[4] In section 6, we consider how generalizations of this basic approach — such as mismeasurement, mark-ups and changing factor shares — affect our findings.

2.2 Data Sources

Outside of computers and software, items for which BEA provides some of the most reliable constant-quality price indexes, our primary source for constant-quality price indexes is Gordon (1990). Gordon collected detailed information on prices and goods' characteristics from sources ranging from mail-order catalogs to articles in specialized magazines like Consumer Reports and Computerworld. Using hedonic techniques as well as more conventional matched-model methods, Gordon constructed quality-adjusted price indexes that offer an alternative to the NIPA price indexes. The result is a set of quality-adjusted chain-weighted price indexes for 22 different categories of producer's durable equipment, covering the period 1947-83. The goods included in Gordon's calculations were classified into four groups:

1. Industrial equipment: Electrical transmission, distribution, and industrial apparatus; Engines and turbines; Fabricated metal products; General industrial

[3] In this simple model, it is irrelevant whether we call q "disembodied" or "embodied" technology. As pointed out originally by Hall (1968), in this type of model the embodied and the disembodied components are not identified separately. Following the bulk of the literature, we refer to changes in q as *investment-specific* technical change.

[4] GHK, Hornstein and Krusell (1996), and Hercowitz (1998) arrive at the same equation in similar setups.

(including materials handling) equipment; Metalworking machinery; Special industry machinery.

2. Transportation equipment: Autos; Aircraft; Railroad equipment; Ships and boats; Trucks, buses, and truck trailers.

3. Other equipment: Agricultural machinery (except tractors); Construction machinery (except tractors); Electrical equipment; Furniture and fixtures; Mining and oilfield machinery; Other equipment; Service industry machinery; Tractors.

4. Office information processing: Office, computers and accounting machinery; Communication equipment; Instruments, photocopy, and related equipment.

This taxonomy of goods reflected the NIPA classification at the time when Gordon was writing. Luckily, the current NIPA classification is similar except for the last group of goods. BEA now distinguishes explicitly among computers and peripherals and other office and accounting machinery. Moreover, since 1999 software is recorded as investment.[5] This last group of goods is now called information processing equipment and software (IPES) and the entire set of 24 investment goods is called nonresidential private fixed investment in equipment and software (E&S).

2.3 Econometric Model

We use simple forecasting methods to extrapolate for the period 1984-2000 the quality-bias implicit in some of the NIPA price series. We use as a benchmark Gordon's computations, which covered the period 1947-83. In addition to providing a longer sample period for statistical analysis, we can see whether there has been an acceleration in technical change in the past two decades that may help explain the surge in the growth rates of GDP and average labor productivity in the late-1990s.

[5] Previously, only software embedded in equipment by the producer of that good was counted as investment. That type of software is still counted as hardware (e.g., Microsoft's Windows operating system already installed on new PCs).

To construct the extended quality-adjusted price series, we update and improve upon the analysis in Krusell, Ohanian, Rios-Rull, and Violante (2000). The key idea exploits the fact that we have a long time series (1947-83) of Gordon's quality-adjusted and of NIPA price indexes. Using these pairs of price indexes, we estimate for each type of asset j an econometric model of Gordon's quality-adjusted price index as a function of a time trend and a cyclical indicator, augmented with the current and lagged values of the NIPA price series of the type:

$$\log\left(p_t^{i_j^*}\right) = c + \beta_1 t + \beta_2 \log\left(p_t^{i_j}\right) + \beta_3 \log\left(p_{t-1}^{i_j}\right) + \beta_4 \Delta y_{t-1} + \varepsilon_t^j, \tag{4}$$

where $p_t^{i_j^*}$ is Gordon's quality-adjusted price index for asset category j, c is the constant, t is the linear time trend, $p_t^{i_j}$ and $p_{t-1}^{i_j}$ are, respectively, the current and lagged value of the NIPA price index, Δy_{t-1} is the growth rate of lagged GDP and ε_t^j is the disturbance. Using the coefficient estimates, we can extrapolate for 1984-2000 the quality-adjusted price level for each asset from the original sample.

A number of econometric issues arise in the choice of the model specification. To begin with, we had to choose the order of integration of the series. We first tested for a unit root in the quality-adjusted and NIPA price index using Augmented Dickey Fuller and Phillips-Perron tests. We could not reject the null hypothesis of a unit root for any of the series.[6] Next, we tested for cointegration between the quality-adjusted and NIPA price series using the Johansen test. For almost all assets we could not reject the null of cointegration at the 10 percent level and for most assets we could not reject at the 5 percent level. From this battery of tests we concluded that the quality-adjusted and the NIPA price series are $I(1)$ and cointegrated. Hence, estimation in levels exploits the long-run comovements of the series and generates a more informative forecast compared to a specification in first-differences.[7]

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[6]Structural breaks could be present in some of the series (e.g., aircraft). It is well known that the existence of breaks biases unit root tests against rejecting the null hypothesis. In the most obvious cases, we judgmentally split the sample in two and tested for a unit root in each subsample. There were no major changes in the results.

[7]We did plenty of sensitivity analysis on the price series for which the evidence on cointegration

We use a time trend, lagged GDP growth, and lags of the NIPA price index in the specification.[8] An alternative specification with lags of the dependent variable would have necessitated multi-step forecasting methods in which the computed forecast of the lagged dependent variable is used recursively. Given the 16-year span over which we need to predict our series, we prefer to anchor our forecast only to actual data.

Our procedure explicitly accounts for the fact that BEA has upgraded its measurement of quality over time. Hence, we do not naively extrapolate the quality-bias in the NIPA price indexes from earlier to later periods. However, the admittedly disputable assumption for the accuracy of our approach is that the data generating process for the quality-bias in the NIPA price indexes has not changed since 1983. For this reason, we do not implement this procedure for most of the goods included in the IPES category, in particular computers and peripherals since BEA provides a reliable constant-quality price index for this category. We also cannot apply our methodology to software, as data on software investment were unavailable to Gordon. Instead, for software we use the NIPA price indexes. By proceeding in this way we minimize the bias that arises if the key assumption underlying our estimation and forecasting methodology is violated.[9]

Finally, the introduction of current and lagged values of the NIPA price variables in our regression implies a trade-off between accuracy in forecasting and a potential endogeneity problem. Our estimates are biased insofar as shocks to quality not controlled for in the regression affect the unadjusted price level. To assess this

was weaker. Notably, we used different specifications of the model in first-differences with very little change in the extrapolated series.

[8]We followed a mixture of Akaike and Schwartz criteria to select the optimal order lag in each equation. In the three case in which more than one lag was statistically significant, we report in Table 1 only the most precisely estimated lag to economize on the presentation.

[9]It is somewhat comforting that extrapolation is also used by BEA and other researchers when better sources of data are unavailable. For example, the NIPA price index for pre-packaged software (which is quality-adjusted) is back-cast from 1985 using a time series equal to 60 percent of the annual change in the NIPA price index for computers and peripherals, which corresponds to the average difference from 1985-97 between the annual rate of change in the computer price index and the pre-packaged software price index. Moreover, some authors such as Jorgenson and Stiroh (2000a) have drawn from the existing empirical results of microstudies on quality improvements in switching gear equipment and spreadsheets to construct constant-quality indexes in order to deflate software and communications investment.

endogeneity problem, we forecasted Gordon's quality bias using only a constant and a trend. When we tried this alternative, our results were not appreciably different for most assets, suggesting such endogeneity is a secondary concern.

2.4 Quality-Adjusted Price Indexes for Industrial Equipment, Transportation Equipment, and Other Equipment

For the 19 goods in these categories we gather the corresponding quality-adjusted price index constructed by Gordon (1990, Appendix B) for the period 1947-83. Then we collect the NIPA price indexes of the investment goods for the period 1947-2000 (Table 7.8, Survey of Current Business). For each category of good j, we select data from the first part of the sample (1947-83) and we estimate an econometric relationship between Gordon's series and the NIPA series, using the model in (4)

Table 1 contains the estimates for each category of goods in industrial equipment, transportation equipment, and other equipment. In the first row, the coefficient on the linear time trend determines the extent of the quality-bias in the NIPA price index. The estimated trend is statistically significant for 15 of 19 assets. The quality-bias is largest for aircraft (15 percent), engines and turbines (6 percent), service industry machinery (about 6 percent), and special industry machinery (also about 6 percent). For metalworking machinery (column 5), agricultural machinery (column 12), electric equipment (column 14), and tractors (column 19) the estimated trend was statistically insignificant indicating that quality-bias in the NIPA price index is unimportant. For these assets, we suppressed the trend and used the estimates reported to extrapolate the series.

2.5 Quality-Adjusted Price Indexes for IPES

Information processing equipment and software (IPES) contains the assets with the fastest rising nominal investment shares and most rapid price declines. To construct a quality-adjusted price index for computers and peripherals, we combine two data sources. First, Gordon provides a quality-adjusted index for computers and peripherals for 1947-83 (Table 6.12, column 2). Second, in 1985 BEA introduced hedonic-based quality-adjusted price indexes for computers and peripherals starting from 1958 (Table 7.8, SCB).[10] We combine these two sources, using Gordon's index from 1947-57 and the NIPA index from 1958 onward.[11]

We exploit the 1999 comprehensive revision of the NIPA that provides price indexes beginning in 1959 for prepackaged software sold commercially, own-account software (software developed internally by firms themselves), and custom software (software tailored to the specifications of firms and purchased externally by these firms). The series for prepackaged software is computed using both matched-model methods and hedonic techniques; the price index for own-account software is based on compensation rates for computer programmers and system analysts and on the cost of the intermediate inputs associated with their work; the price index for custom software is computed as a weighted average of the first two indexes.[12] The price of pre-packaged software has been falling at the fastest rate (11 percent per year). This rapid decline has contributed to the slowdown in the rise of the overall quality-adjusted price of software: from 2 percent in the period 1959-78 to virtually zero since then.[13]

There are a few studies that can be used to check the adjustment BEA makes for prepackaged software. Brynjolfsson and Kemerer (1996) report that the quality-adjusted price of spreadsheets falls at an annual rate of 16 percent from 1987 to

[10] Even before 1985 BEA tried to measure quality change in a number of ways using, for example, "matched-model" methods. Matched-model methods would seem inadequate when product variety expands rapidly. However, Aizcorbe, Corrado and Doms (2000) find that matched-model and hedonic price techniques show very similar price declines for computers from 1994 to 1998.

[11] Krusell et al. (2000) exploit the large empirical literature on the derivation of quality-adjusted price indexes for computers and peripherals to extend the Gordon series to 1992. As an alternative, we also constructed a constant-quality index for computers and peripherals using Gordon's price series until 1983 and the Krusell et al. series thereafter. The resulting price index and our benchmark index are similar in the first half of the sample: for both series the average decline rate of the quality-adjusted price is around 16 percent from 1947 to 1973. However, in the second part of the sample, the benchmark series declines at an annual average of 17 percent whereas the Gordon-Krusell series declines at an annual average of 20 percent. The difference is concentrated in the late-1980s and the early-1990s. Overall, our benchmark price index provides a conservative estimate of quality improvement in computers and peripherals.

[12] The methodology used to construct these indexes is described in detail in Parker and Grimm (1998).

[13] The aggregate price series for software investment is the Tornquist aggregate of the three price series using their respective nominal investment shares as weights.

1992. This is slightly faster than the 15 percent decline estimated by Gandal (1994) for 1986-91. The average rate of change of the BEA price index for prepackaged software is 13 percent per year in the comparable period, suggesting that the quality-adjustment in the NIPA data may be fairly accurate.[14] Nevertheless, the fact remains that prices for the other two categories of software are almost certainly overstated substantially. In the absence of a comprehensive alternative, we take a conservative approach and use the NIPA price index for software.

Communications equipment and instruments are the other goods for which we would expect rapid price declines. Unfortunately, systematic studies of the quality-bias in the BEA price index have yet to be done: BEA has adopted a constant-quality index only for digital switching equipment which is a subcategory of communications equipment (Grimm, 1997). However, the quality of other fast-growing types of telecommunications equipment has improved vastly (e.g., fiber-optic cables). Therefore, we use the same forecasting procedure we applied to the goods outside IPES and report in Table 1 the results for communications (column 20) and instruments (column 21). Our estimated constant-quality price indexes for communications equipment and for instruments decline at an annual rate of nearly 7 percent and nearly 5 percent, respectively. By contrast, their NIPA counterparts reflect very little change.

Finally, since Gordon's work does not contain a quality-adjusted series for office and accounting equipment goods other than computers, for this set of goods we simply use the NIPA series (Table 7.8, SCB). It is clear that this conservative choice will have only a small effect since this type of investment accounts for a tiny and shrinking share of nominal E&S outlays.

[14] The fact that the BEA number is slightly lower may be attributable to the fact that prepackaged software does not include only spreadsheets. Oliner and Sichel (1994) estimate a 3 percent annual price decline during an earlier period for a bundle of prepackaged software programs including spreadsheets, word processors and databases. Hence, evidence suggests that the price decline for software other than spreadsheets has been slower.

2.6 Quality-Adjusted Price Index for Consumption

We rely entirely on the NIPAs for a constant-quality price index for consumption. Our preferred price index is constructed with the prices of nondurable goods (excluding energy expenditures which can be exogenously affected by fluctuations in the price of petroleum) and non-housing services (from Table 7.5, SCB), weighted by their respective shares (from Table 2.2, SCB) through a Tornquist procedure. As a very basic way to assess the robustness of our results, we compared our preferred price index to others that include, in turn, energy expenditures, housing services and residential structures. Despite our concern, the movement of these various price indexes is remarkably similar and they all grow at an annual rate of just less than 4 percent.

3 Empirical Results

3.1 Quality-Adjusted Price Index for E&S

We use the Tornquist procedure to aggregate the asset-level price indexes into a quality-adjusted price index for E&S. We first compute the nominal investment shares of each asset for each year. The share of asset j is the ratio of the current dollar value of investment in asset j and the current dollar value of total private nonresidential E&S investments (Table 5.8, SCB). Let $s_t^{i_j}$ be the nominal share for investment good $j \in \{1, 2, \ldots, 24\}$ and let $p_t^{i_j^*}$ be the corresponding quality-adjusted price index for investment of type j. Then the change in the aggregate quality-adjusted price index for E&S is

$$\Delta p_t^{i_e^*} = \sum_{j=1}^{24} \log \left(\frac{p_t^{i_j^*}}{p_{t-1}^{i_j^*}} \right) \left(\frac{s_t^{i_j} + s_{t-1}^{i_j}}{2} \right), \tag{5}$$

and the level of the price index is recovered recursively

$$p_t^{i_e^*} = p_{t-1}^{i_e^*} \exp(\Delta p_t^{i_e^*}).$$

By comparing the growth rate of the quality-adjusted price index for E&S in equation (5) to the NIPA price index for E&S we can compute the quality-bias in the NIPA price index. Recall that this bias arises because we use for 21 of the 24 categories of E&S constant-quality price indexes that decline more rapidly than the comparable NIPA price indexes. According to our estimates, the average annual quality-bias is about 2.5 percent over the sample period. Perhaps surprisingly, the quality-bias is about the same in the 1980s and 1990s when computers and software — for which we rely on the NIPA deflators — are a growing share of investment. The reason is that there is a great deal of quality-bias in some fast-growing categories like communications equipment. This effect approximately offsets the smaller quality-bias stemming from an increase in the share of computers and software.

3.1.1 Robustness Check

Our methodology explained Section 2 is silent about the mechanism that generates quality improvement. In this volume, Wilson argues that R&D determines the rate of quality improvement. As a robustness check, we replaced the time trend in equation (4) with the log of the R&D capital stock for 10 different types of equipment from 1957–97.[15] In the bottom panel of Table 1, we also report results using the overlapping sample of Gordon's quality-adjusted price data and Wilson's R&D data. The coefficient estimates on the log of the stock of R&D is statistically significant for 8 of the 11 types of equipment.

Using the estimates from this alternative specification, we extrapolate the quality-adjusted price until 1997 and aggregate the asset-specific price indexes using the Tornquist procedure described in equation (5). The annual rate of decline for the resulting price index is 2.2 percent in the period 1984-97, which compares to a decline of 2.5 percent from our baseline estimation. Severe trend breaks in the R&D series for transportation equipment goods — the stock of R&D for aircraft falls by almost 10 percent per year between 1993 and 1997 and the stock of R&D for trucks, buses, and truck trailers falls by 15 percent per year from 1987 to 1997 — account

[15] We thank Dan Wilson for providing us with the data. The reader should refer to Wilson's article for a detailed description of the R&D data and the mapping between product fields and BEA asset categories.

for the slower growth rate. Hopefully, additional research will isolate the source of these sudden plunges in the R&D capital stock data.

3.2 Indexes of Investment-Specific Technical Change

3.2.1 Aggregate Index

Our aggregate index of the state of technology for E&S is

$$q_t^e = \frac{p_t^{c^*}}{p_t^{i_e^*}}, \tag{6}$$

where $p_t^{c^*}$ is the consumption price index. In Figure 1, we plot the aggregate rate of investment-specific technical change Δq_t^e as the solid line. Two important findings emerge: first, technical change grows rapidly — at an annual average of 4 percent — in the postwar period; second, since the mid-1970s the pace of technological improvement has accelerated: the index grows at an annual rate of about 3 percent until 1975 and at an annual rate of 5 percent thereafter.[16] In the 1990s the growth has been spectacularly high, reaching an average annual rate in excess of 6 percent. We postpone discussing the dashed line in Figure 1 — an alternative measure of technical change that adjusts for factor share bias — until section 6.

Not surprisingly, our baseline estimate of the annual growth rate of technical change is similar to Hulten's (1992) estimate of 3.4 percent for the comparable period, 1949-83. Hobijn (2000) calculates the rate of embodied technical change by calibrating a vintage capital model. According to his computations, the average annual growth rate of embodied technical change in equipment and structures is 2.5 percent. When we include structures in our index and assume conservatively that structures have no quality improvement, our comparable estimate of the growth rate is 2.6 percent: not only are the annual averages very similar, the time pattern of the two series is similar as well. The production function approach used for example by

[16] We have excluded the 1975 outlier from both sub-samples. This outlier is present even in the original Gordon's data and, to a large extent, is attributable to the fact that some of his data sources for 1974 were still affected by price and wage controls, lifted a few months later. In the absence of better information on prices, we have left this entry unchanged, but the reader should be aware that the sharp drop in the series in 1975 does not reflect (negative) technical change.

Bahk and Gort (1993) and Sakellaris and Wilson (2000) on plant-level data yields estimates of the growth rate of capital-embodied technical change between 12 and 18 percent per year, much larger than our estimate.

3.2.2 Asset Indexes

The index of the state of technology for a specific asset j is constructed as

$$q_t^j = \frac{p_t^{c^*}}{p_t^{i_j^*}}. \tag{7}$$

Table 2 reports the pace of technical change in each of the 24 asset categories as well as for the components of software. Not surprisingly, the largest gains are in IPES: productivity improvements for computers increased at an annual average of 23.5 percent, with a peak growth rate of 26.5 percent in the 1960s and in the 1970s. Technical change in prepackaged software also advanced at a swift pace, increasing at an annual average of 15 percent over the period, with a peak growth rate of 18 percent in the 1970s. Interestingly, for both computers and software there was a slight deceleration in the pace of growth in the 1980s and the 1990s compared to the previous decade. The productivity level of communication equipment advanced at an annual average of 9 percent in the postwar period. In contrast to computers and software, the 1990s witnessed a sharp acceleration in the rate of growth for communications, reaching 13 percent. The productivity level of aircraft also advanced rapidly, at an annual rate of 9 percent and 11 percent in the last two decades. At the same time, there are categories with very little technical change, such as agricultural machinery, metalworking equipment, and own-account software.[17]

A careful review of Table 2 shows that in most categories outside IPES productivity growth accelerated only in the 1990s. One possible interpretation of this pattern is that in a first phase (1970s and 1980s) productivity advancements were concentrated in IPES goods, while later (in the 1990s) the new technologies started

[17] As explained earlier, for own-account software we use the NIPA price index which is not quality-adjusted.

to be applied to a much wider range of goods beyond IPES, fully displaying the "general purpose" nature of the new technology.

3.2.3 Industry Indexes

We also construct measures of technical change at the two-digit and finer industry level using BEA's detailed estimates of E&S investment by industry and type of asset, which are based on a variety of source material including the input-output tables.[18] Our industry-level measures of technical change are obtained through the same Tornquist aggregation procedure we adopt for the economy-wide index in equation (5), where each asset-specific constant-quality price index is weighted by the industry-level nominal expenditure shares for that asset.[19] These indexes measure the rate of technological improvement in the typical mix of investment goods used in production by each industry.

Table 3 documents the growth rates of technical change for 11 major industries by decade. Wide variation in the growth rates is apparent: quality improvements in investment goods used in the communications industry advanced at an 8 percent annual rate during the postwar period, while agriculture, forestry and fishing experienced a relatively dismal 1 percent annual growth rate.[20] To appreciate such heterogeneity, in Figure 2 we plot the annual distribution of technical change — 90th percentile, median, mean and 10th percentile — using the most detailed classification of 62 industries available using our data. Each industry-year observation is weighted by the nominal industry investment share that year. Two findings stand out from Figure 2: first, there is a lot of heterogeneity across industries as evidenced by the 6 percentage point annual average difference between the 90th and 10th percentiles of the distribution; second, over the years this differential has remained

[18] The data are available from www.bea.doc.gov/bea/dn/faweb/Details/Index.html.

[19] The implicit assumption in this procedure is that the bulk of the variation in rates of technological change across industries can be attributed to the different mix of investment goods *between* our 24 categories rather than *within* each category.

[20] The negative estimate for Agriculture, Forestry, and Fishing in the 1970s reflects intensive use of tractors, which are estimated to have negative rates of technical change for a number of years in the 1970s.

quite stable and has moved in tune with the mean which suggests that the IPES-led technological acceleration that began in the mid 1970s had a general impact, reaching virtually every industry in the economy.

As another way to assess the general impact of IPES, we calculated the transition probability for industries within the distribution. In the last two decades, the persistence of an industry's relative position in the distribution has increased significantly.[21] This suggests that productivity improvements in the best-practice technology are more the result of an aggregate shock, rather than industry-specific shocks. Taken together, our findings confirm the idea that IPES is a "general purpose" technology.

3.3 Quality-Adjusted E&S Capital Stock

We create a quality-adjusted investment series i_{et}^{*} by dividing nominal E&S investment by the quality-adjusted price index $p_t^{i_e^*}$. Then we construct the aggregate quality-adjusted productive capital stock of E&S k_{et}^{*} using the perpetual inventory method and a constant geometric rate of depreciation:

$$k_{et}^{*} = \left(1 - \delta_t^e\right) k_{e,t-1}^{*} + i_{et}^{*}, \tag{8}$$

where δ_t^e is the time-varying physical depreciation rate.

As Oliner (1993), Gort and Wall (1998) and Whelan (2001) show, *physical* depreciation must be used to construct the quality-adjusted productive capital stock when investment is measured in efficiency units. Largely as a result of Oliner's research, BEA began to construct its capital stocks correctly, but only for the assets Oliner studied, mainframes and peripherals. For every other type of asset, BEA continues to construct capital stocks using economic depreciation. This causes the capital stock to be mismeasured, especially for the types of assets that are subject to rapid quality improvement over time, such as PCs, prepackaged software and

[21] If we divide the cross-industry distribution of technical change into quartiles and weight each industry by its nominal investment share, the diagonal elements of the transition matrix are on average 0.45 during the postwar period, rising to 0.70 during the 1990s.

communication equipment.[22]

BEA reports economic depreciation rates by asset d_t^j (Tables A-B-C in BEA, 1999). Parker and Grimm (2000) report the depreciation rates BEA uses for software: 55 percent for pre-packaged software and 33 percent for own-account and custom software. Fraumeni (1997) describes the methodology for calculating these depreciation rates: in most cases, BEA still uses the numbers created by Hulten and Wykoff (1981), which include both physical decay and obsolescence. Economic depreciation for an asset of type j is defined and measured by BEA as the change in the value of an asset associated with the ageing process, so it consists of a pure age effect and a time effect. The age effect captures physical decay δ_t^j due to wear and tear and the time effect captures obsolescence due to the change in the relative price of the asset in the period, q_t^j/q_{t-1}^j. Thus,

$$d_t^j = 1 - \left(1 - \delta_t^j\right) \frac{q_{t-1}^j}{q_t^j}. \tag{9}$$

Obviously, when there is no technical change, economic and physical depreciation are identical. However, when technology improves, economic depreciation exceeds physical depreciation. Using the identity in equation (9), we separate the physical decay component δ_t^j from the BEA measures of d_t to appropriately construct the aggregate series for k_{et}^*.

For each asset category j, we use the official depreciation rates and equation (9) — where we measure q_t^j from equation (7) — to back out the actual physical decay rate δ_t^j. As suggested by Whelan (2000), we then aggregate these physical depreciation rates in each year using the nominal capital shares of each asset in the total E&S capital stock s^{k_j} (we compute these nominal capital shares from the BEA Fixed Assets Tables), in order to obtain a series for the physical depreciation rate

[22] The Bureau of Labor Statistics (BLS) measures of the productive capital stock suffer from a similar problem and so do the capital stocks constructed by researchers who follow the lead of BEA and BLS. Although BLS uses a hyperbolic depreciation rate rather than a geometric one, they tune the hyperbolic profile so that it is consistent with BEA's geometric rate of economic depreciation. To understand how wrong the calculations may be, keep in mind that BEA and BLS construct their capital stocks of prepackaged software based on a 55 percent depreciation rate.

in E&S δ_t^e,

$$\delta_t^e = \sum_{j=1}^{24} \delta_t^j s^{k_j}.$$

Figure 3 plots three series: the official economic depreciation rate d_t^e, our computed series for physical depreciation δ_t^e, and a polynomial-smoothed version of our series.[23] The BEA rate of economic depreciation rises from 12 percent in the 1950s to over 15 percent at the end of the sample, while our estimated series, although very volatile because of the variability implicit in our measures of technical change, looks trendless at 10 percent. Hence, the gap between economic depreciation and physical depreciation that opened up in the mid-1970s can be attributed to losses in the value of assets because of faster obsolescence. The rise in the importance of the obsolescence component over time is principally due to the increasing share of IPES in the capital stock. To parallel the practice of the BEA of using constant depreciation rates, even for long periods, in what follows we always use our smoothed series. Perhaps surprisingly, we found that our quantitative results were little affected using the non-smoothed physical depreciation rates.

In Table 4 we compare the growth rates of our quality-adjusted capital stock Δk_e^* and the BEA capital stock Δk_e^{BEA}. Our capital stock of E&S, which is based on quality-adjusted investment flows and physical depreciation, grew at an annual average rate of 8.8 percent in the postwar period. By contrast, the BEA capital stock, which is based on quality-adjusted investment flows for a subset of assets and economic depreciation, grew at an annual average of 5.8 percent in the postwar period. About 80 percent of the difference between the growth rates is due to missing quality-adjustment in the BEA price indexes. The residual is due to the presence of obsolescence in the official depreciation rates.[24]

[23]We do not filter out the obsolescence component from mainframes and peripherals, as the BEA depreciation rates for these goods are net of this component (see Oliner 1993 for details). For autos and PCs, BEA does not report a geometric depreciation rate, but rather an age-dependent depreciation schedule. We approximate these with a constant geometric rate of 25 percent and 40 percent per year, respectively.

[24]We also computed the difference between the growth rate of our series and the growth rate of a series constructed using investment valued in terms of consumption and economic depreciation. The overall difference between the annual growth rate of our series and this alternative series is

Given the emphasis on the role of IPES capital in explaining US growth in the past decade, it is interesting to compute the dynamics of the IPES capital stock. As a by-product, we can use this quality-adjusted IPES capital stock as a separate factor of production in our growth decomposition. In order to compute a rate of physical decay for the stock of IPES goods, we repeat the same procedure outlined above. Our estimated depreciation rate is substantially lower than the NIPA series (the difference is 5 percentage points at the beginning of the sample and 7 percentage points at the end of the sample); moreover, our implied rate of physical decay displays a rise at the beginning of the 1980s (from 13 to 16 percent), consistent with BEA's claim that the physical depreciation rate for computers and peripherals increased from 27 percent to 31 percent after 1978.[25] The resulting quality-adjusted productive capital stock for IPES reported in Table 3 grows at an annual average of 16.3 percent over the sample, compared to an annual growth rate of the BEA series of 12.3 percent. The decomposition of this differential between quality-adjustment of the investment flows (namely communications and instruments, as for all other IPES goods we have used BEA data) and the presence of obsolescence in economic depreciation yields about the same 80-20 split as the decomposition for aggregate E&S.

3.4 Structures Capital Stock

For growth accounting, we need to integrate the structures capital stock into our framework. To deflate nominal investment in structures, we use the NIPA price indexes for 19 different categories of structures. On aggregate, this price index for structures grew just a little faster than the price index for consumption in the

3.7 percent. Gort and Wall (1998) show that if both the physical decay rate δ^e and the rate of obsolescence Δq (technical change) are constant, then the difference between the two series should be exactly Δq, which is 4 percent for our series. Thus, given that δ_t^e is about flat, the 0.3 percentage point differential is from the large variation of Δq_t.

[25] Although computers and software have very high depreciation rates, the overall depreciation rate (even before accounting for obsolescence) for IPES is much lower because computers and software represent a small share of the capital stock: until the early-1990s computers and software constituted less than one-third of the total stock of IPES goods.

postwar period, which implies that there was no appreciable quality improvement in structures. However, according to Gort, Greenwood and Rupert (1999), structures-embodied technical change advanced at an annual rate of 1 percent in the postwar period. Hence, we might underestimate the growth rate of structures by using the NIPA price indexes. Nevertheless, in keeping with our conservative approach, we use the NIPA price indexes.

Creating an aggregate stock of equipment and structures in efficiency units (k_t^*) takes three steps. First, we construct a price index for total business fixed investment by weighting the two price indexes for E&S and structures by their nominal investment shares. Second, we calculate a physical depreciation rate for business fixed investment. In doing so, we compute an average depreciation rate for structures of about 3 percent per year.[26] Finally, we construct the aggregate capital stock using the perpetual inventory method and a constant geometric rate of physical depreciation.

4 Growth Accounting

4.1 "Statistical" Growth Accounting

Using statistical growth accounting we can attribute the growth in real GDP to the share-weighted growth in inputs and, in particular, to quality improvement in capital goods. It is straightforward to show that our simple theoretical model in Section 2.1, together with equation (8) can be interpreted as a one-sector growth model with an aggregate production function. In our accounting framework, we use a Cobb-Douglas specification for the production function and we measure real GDP in constant-quality consumption units. We focus on the domestic private business sector of the US economy. A standard computation yields a labor share with an average value of 0.64 for the period 1947-2000. We measure real GDP growth in the

[26] We compute this number by aggregating asset-specific BEA depreciation rates with their nominal capital stock shares. Gort, Greenwood and Rupert separate the obsolescence component from economic depreciation and estimate a physical rate of decay of about 2 percent per year. This is consistent with our number, given Gort, Greenwood and Rupert's estimate that there is 1 percent unmeasured technical change embodied in structures.

private business sector directly from NIPA (Table 1.8, SCB).

When decomposing the sources of real GDP growth, we distinguish between the contribution made by the quality of capital (Q_t) and by the quantity of capital $\left(\tilde{k}_t\right)$. The quantity of capital is measured in terms of constant-quality consumption units. The quality of capital is measured as the ratio of the quality-adjusted capital stock (k_t^*) and the capital stock measured in terms of constant-quality consumption: $Q_t = k_t^*/\tilde{k}_t$. Hence, the quality of capital isolates the contribution to real GDP growth from our quality-adjusted investment price indexes.[27] To measure labor input l_t, we use the quality-adjusted index created by Ho and Jorgenson (1999, Table 5) which allows us to distinguish between quantity of labor (hours worked n_t) and quality of labor (h_t), with $l_t = h_t n_t$.[28]

Our statistical growth accounting is based on decomposing real GDP growth Δy_t into the share-weighted growth in inputs

$$\Delta y_t = (1-\alpha)\Delta h_t + (1-\alpha)\Delta n_t + \alpha\Delta\tilde{k}_t + \alpha\Delta Q_t + z_t,$$

where α denotes the capital share. In Table 5, we report the results of the statistical growth accounting for a variety of periods.[29] In the postwar period, the total contribution of capital to real GDP growth is nearly 54 percent, whereas the contribution of labor input is 32 percent. TFP growth accounts for the remaining 14 percent of growth. The contributions of both capital and labor grow steadily over the sample period at the expense of TFP, which has a negative contribution in the last 20 years.

Out of the 54 percent average contribution of capital, about 20 percent is due to quality improvement in total capital. In the 1990s the contribution jumps to more

[27] Notice that the quality of capital we measure is not the usual one, defined as the difference between capital services and capital stocks created with NIPA price indexes. That difference measures the composition effect of moving toward assets with short service lives and, hence, high estimated productivity during each year of service. In future research, we plan to combine approaches by constructing the capital services of our quality-adjusted capital stock.

[28] Ho and Jorgenson's index is constructed for total private sector, including business sector, private households and non-profit institutions. Private households are not a major source of employment, but there remains a slight discrepancy between our output measure and the labor index due to the non-profit sector.

[29] We begin in 1948 and end in 1999 because the labor index constructed by Ho and Jorgenson spans that period.

than 30 percent. Since the contribution of every other factor falls or is about flat in the 1990s, our findings indicate that the jump in the quality of capital in the 1990s explains the resurgence in real GDP growth. As we would expect, the contribution of productivity improvement in IPES capital grows enormously over the sample, from just 1 percent in the 1950s to over 12 percent in the 1990s, averaging 6 percent in the postwar period.[30] By contrast, the contribution of worker quality was very high in the 1950s, but it falls sharply in the 1980s and the 1990s, possibly because of the entry of the baby-boom cohorts in the late 1970s and because the strong labor market of the 1990s absorbed predominantly workers from the lower part of the skills distribution.

A number of authors (e.g., Hulten, 1992, Jorgenson and Stiroh, 2000a, 2000b) argue that GDP should be quality-adjusted in proportion to the division between consumption and investment. For comparability, we create a Tornquist price index from personal consumption expenditures (Table 10.1, SCB) and from business fixed investment, where we use our quality-adjusted price index for the latter component. Real GDP growth computed in this way is on average 0.3 percentage points greater than GDP measured in constant-quality consumption units, but this difference is twice as large in the 1990s. As a result, we find that the contribution of capital and labor is smaller in the 1990s, implying a larger contribution of TFP, which is no longer negative. The TFP contribution remains positive in the 1980s and increases substantially in the 1990s. We analyze the effect of this pick-up on labor productivity in the late-1990s in more detail in Section 4.3.

Hulten (1992) found that embodied technical change explained 20 percent of growth in manufacturing sector output from 1949-83. Our comparable estimate for the whole economy is much higher, nearly 40 percent in the same period. Jorgenson

[30] To identify the contribution of growth in IPES goods for the growth of the aggregate capital stock between time t and t', we use the Tornquist decomposition

$$\Delta k_{t-t'} = \frac{\left(s_t^{k_{ipes}} + s_{t'}^{k_{ipes}}\right)}{2} \Delta k_{ipes,t-t'} + \frac{\left(s_t^{k_{other}} + s_{t'}^{k_{other}}\right)}{2} \Delta k_{other,t-t'}$$

where s_t denotes the nominal share in the total capital stock at time t.

and Stiroh (2000a, Table 2) report the contributions of various inputs for the period 1959-98: in their calculations the quantity of capital contributes 36 percent, capital-embodied quality improvement contributes 13 percent, and labor input contributes 34 percent. This implies TFP accounts for 17 percent of growth. Despite the fact that we find a similar contribution for capital in efficiency units, our estimates suggest that a much larger fraction is due to quality. We also compute the contribution of labor to be roughly 3 percentage points smaller, which boosts up by the same amount our estimate of the share of TFP growth.

4.2 "Equilibrium" growth accounting

One disadvantage of statistical growth accounting is that it does not isolate the underlying sources for capital accumulation. As a result, such growth accounting is silent about whether, for example, the quantity of capital increased because there were advances in the productivity of new investment goods or because of TFP. By contrast, a structural equilibrium model can be used to solve for the optimal investment policy rule as a function of the underlying sources of growth of the economy.

Our economy displays three sources of growth in per capita income (or labor productivity y_t/n_t): technical change in producing capital q_t, quality improvement in labor h_t, and total factor productivity z_t. Assuming that all three sources of growth are exogenous, it is a simple exercise to use the solution of an equilibrium model to attribute income per capita growth entirely to the three sources.[31] We find that technological advance in producing capital dwarfs the other two sources of growth: 60 percent of growth from 1948-99 is explained by quality improvement the production of capital, 25 percent is due to improvements in the quality of labor (essentially linked to the rising educational attainment of the population), and the residual 15 percent is due to neutral technical change. Our results are in line with the equilibrium growth accounting exercise of GHK who quantified the contribution

[31] In a mathematical appendix available from the authors we derive the model we use for the calculations.

of q_t for the whole economy to be 58 percent from 1954–90.[32]

4.3 Productivity Surge in Late-1990s: Cycle or Trend?

The performance of the US economy in the second half of the 1990s has been remarkable. According to our calculations, real GDP growth in the private sector averaged 5.2 percent per year from 1995 to 1999, while the average in the preceding two decades was just below 3.5 percent. This large acceleration in real GDP growth has generated a debate among economists about (1) whether IPES investment drives the acceleration, and (2) whether the upturn is cyclical or structural.

Jorgenson and Stiroh (2000a) and Oliner and Sichel (2000) suggest that IPES investment is key to the productivity acceleration of the late 1990s. For example, Oliner and Sichel compute that over 40 percent of the labor productivity acceleration of the late-1990s compared to the 1973-95 period is due to capital deepening from IPES investment. Jorgenson and Stiroh's computations imply a somewhat smaller figure, around 35 percent. In both calculations, TFP accounts for the remaining growth, with labor quality playing a very small role.[33] Both studies document that the TFP acceleration is large even in industries that do not use IPES intensively. However, neither study attempts to disentangle the cyclical and structural components of the upswing. Gordon (2000) offers a more skeptical view about the role of IPES investment. According to Gordon, more than one-third of the labor productivity resurgence of the late 1990s is a cyclical phenomenon. Moreover, he finds that the bulk of disembodied productivity acceleration is concentrated in IPES-intensive industries, with other industries gaining little if anything from the "IT revolution".

In Table 6, we report our own decomposition of the increase in the grwoth rate of labor productivity in the late-1990s. For this exercise, we use real GDP constructed with a price index that includes our constant-quality investment price index, as in

[32]Our data imply that the contribution of q_t in the GHK sample period is slightly lower of what they found, around 54 percent. We attribute a much smaller role to the residual component z_t, because they did not account for quality improvements in labor input.

[33]Both studies report that capital deepening outside of IPES categories has decelerated and therefore has contributed negatively.

the right panel of Table 5. We distinguish among capital deepening, labor quality changes, and TFP. According to our calculations, the growth rate of labor productivity increased from an annual rate of 1.77 percent in 1973-94 to an annual rate of 2.64 percent in 1995-99, a pick-up of 0.87 percentage point. This is a somewhat smaller increase than reported by Gordon (2000) and by Oliner and Sichel (2000), but closer to Jorgenson and Stiroh (2000a) and BLS. The first column confirms that capital deepening helps drive the recent increase, contributing over 42 percent. This number hides a difference with the previous studies: in our calculations, IPES accounts for only 25 percent of the total productivity surge whereas other investment goods contribute the rest. It is worth noting that the entire surge in capital deepening is due to quality improvement, with the quantity of capital measured in consumption units contributing negatively. Consistent with other studies, we find that the dominant force in the increase in labor productivity growth is TFP.

To analyze whether the increase is temporary or permanent, we split each component of labor productivity into cycle and trend using a Hodrick-Prescott filter. The commonly used smoothing parameter for annual data is $\lambda = 100$, but recently Ravn and Uhlig (2001) argue that the best choice is $\lambda = 6.25$ which implies a more volatile trend component. Thus, with a lower λ we would expect to obtain a lower bound for the cyclical component. We find that the cyclical component of the increase in labor productivity growth is bounded between 30 percent and 90 percent. Hence, Gordon's estimate of one-third could well be conservative.[34] From Table 6, we also conclude that the deceleration in labor quality is mostly a cyclical phenomenon (probably associated with a strong labor market that drew from the bottom tail of the skills distribution), while the acceleration in the quality of capital is a structural phenomenon. The large gap between the upper and lower bound in the estimation of the cyclical component is linked to TFP: the data cannot disen-

[34]This is the cyclical component for the period 1995-99 extracted filtering the whole series for the period 1948-99. There are two reasons why this could be an inaccurate estimate: first, the business cycle was not completed in 1999 because real GDP had not reached a turning point; second, any filter tends to be more imprecise at end-points.

tangle whether the surge in TFP belongs to the cycle or to the trend. The answer to this question will help determine whether the strong labor productivity performance of the US economy will extend beyond the typical length of an expansion.

5 Technological Gap and Its Effects

5.1 Technological Gap Between Productivity of New Vintages and Average Practice

Hulten (1992) shows that quality-adjusted price indexes can be used to measure the "technological gap" between the productivity of new vintages and the average practice in the economy. Let the average efficiency level of E&S be $Q_t^e = k_{et}^* / \widetilde{k}_{et}$, where k_{et}^* is the quality-adjusted stock of E&S and $\widetilde{k}_{et}$ is the stock of E&S measured in constant-quality consumption units. Then the technological gap is given by the following expression

$$\Gamma_t^e = \frac{q_t^e - Q_t^e}{Q_t^e}. \tag{10}$$

The dynamics of this index are determined by the speed of the leading edge technology relative to the pace of investment growth.[35]

Figure 4 plots the evolution of Γ_t separately for E&S and for IPES. The technological gap for E&S was about 10 percent in the 1950s, rising to 20 percent in the 1960s. After holding steady in the 1970s, the gap rises again in the 1980s and 1990s, when it reaches 40 percent. This represents a truly amazing upsurge in the average technological gap in the economy.[36] Interestingly, although the gap for IPES is always greater than that for E&S, the difference between the two opens up dramatically from the mid-1970s to the mid-1980s. The difference evaporates in the 1990s when the technological gap in IPES remains about constant. This pattern can be explained by the substitution between different types of E&S following

[35] Hulten calls this measure the "elasticity of embodiment" because it also measures how investment in the frontier technology feeds back into the growth rate of the average level of efficiency.

[36] Hulten (1992) computed estimates of Γ_t for only the manufacturing sector. He reports an average value of 23 percent for the period 1949-83, and 22 percent for the sub-period 1974-83. For the same sample periods, our estimates are 17 percent and 20 percent, respectively. The differences can be attributed to many factors: including updated estimates for computer and software investment, sectoral differences, different rates of depreciation used to construct the capital stock.

the sharp changes in their relative quality-adjusted prices. The period 1975-85 witnessed phenomenal technological advances in IPES, but these technologies were not yet widespread in the workplace. Firms started substituting to IPES from other equipment, thus investment in IPES started to grow rapidly. As a consequence, the technological gap for IPES closes down gradually.

Figure 5 plots the distribution of the technological gap for E&S in our 62 industries. Although the increase in technological gap for the economy depicted in Figure 4 is evident at every quantile of the industry distribution, Figure 5 shows a rise in the difference between the 90th and 10th quantile over time. In 1968, the technological gap of the 90th percentile was 30 percent and the technological gap of the 10th percentile was 10 percent. Thirty years later, these two numbers are 55 percent and 20 percent, respectively. Given that the productivity of new vintages accelerated at about the same rate across all 62 industries (see Figure 2), this latter finding suggests that the speed of adoption of new technologies has been very different across industries. This is confirmed by comparing the technological gaps by 11 major industries in Table 7. In the 1990s, for example, the technological gap in communications was 60 percentage points greater than in agriculture, forestry and fishing.

5.2 Adoption of New Technologies and Returns to Human Capital

Although a thorough examination of the different patterns of adoption across sectors is beyond the scope of this paper, a deeper look at the aggregate data is a useful first step. In their influential paper, Nelson and Phelps (1966) conjecture that "[T]he rate at which the latest, theoretical technology is realized in improved technological practice depends upon educational attainment and upon the gap between the theoretical level of technology and the level of technology in practice" (p. 73). In terms of our notation, the discrete-time version of their equation (8) at the aggregate level is

$$\Delta Q_t = \phi(h_{t-1})\Gamma_{t-1}^{\theta}, \tag{11}$$

where $\phi(h_{t-1})$ is an increasing function of human capital stock in period $t-1$ and ΔQ_t is the growth rate in the average practice between period $t-1$ and period t.[37] Given that we have data on Q_t, Γ_t, and human capital we can estimate equation (11) using OLS by taking logs and appending a stochastic error term, which we assume is orthogonal to the regressors. Ho and Jorgenson (1999) construct an index of the quality of the labor force in the US in the postwar period based on several dimensions: age, education, gender, and occupation. When we estimate equation (11), we enter each of these different measures of human capital: age is proxied by the share of young workers aged 16-24, education by the share of college graduates, gender by the share of female workers, occupation by the share of self-employed. The results of the estimation are reported in Table 8.

The coefficient on Γ_{t-1} in column (5) is about 0.7 and statistically significant from zero. By itself our measure of the technological gap captures roughly 85 percent of the variation in the growth rate of the average practice over time (column (1)). The residual 2 percent is explained by human capital: the shares of young workers, and college educated workers are positively associated with more rapid adoption of new technology, while the fraction of self-employed workers is not statisitically significant. Hence, certain observable measures of "adaptability" do determine whether new technology is adopted, but they do not explain a large fraction of the time-series variation. Nevertheless, the coefficient on the skilled share is remarkably high: a 1 percentage point increase in the share of college-educated workers induces a 10 percent acceleration in the speed of adoption (i.e., the growth rate of Q_t rises by 10 percent). More puzzling at first is the negative and significant estimate on the share of women in the labor force. Labor force participation of women has increased massively: in 1950 women accounted for less than one-third of the labor force, while in 1999 the share of women was close to 50 percent. Many models of labor force participation imply that the rise in participation rates takes place from the top of

[37] We slightly generalize the adoption equation by introducing the parameter θ which measures the elasticity of the growth in average practice to the technological gap. In Nelson and Phelps' original formulation θ is restricted to equal 1.

the ability distribution. Thus, the share of women is negatively correlated with the average level of unobserved ability among women and therefore in the workforce. According to this interpretation, the negative sign in the regression picks up the fall in unobserved ability and suggests that the latter is an important determinant of technology adoption.[38] Since our first pass at the aggregate data is so encouraging, in future research we plan to estimate the adoption equation at the industry level.

Another implication of Nelson and Phelps' adoption equation (11) is that a larger technological gap increases the marginal productivity of skilled workers and hence their relative wage. The time-series behavior of the technological gap for E&S squares with the well-known facts on wage inequality. The gap increases steadily except when it levels off during the 1970s, which is the only decade in the postwar period during which the education premium fell. In Figure 6, we compare the returns to college education from Goldin and Katz (1999) and a smoothed version of the technological gap for E&S plotted in Figure 4.[39] The two series move together at low frequencies, consistent with the idea that the technological gap may be an important force driving the skill premium.

6 Robustness

Our basic approach abstracts from a number of potentially important considerations. Paramount among these is how our measures of technical change would be affected by changing factor shares, mismeasurement of constant-quality consumption, and ignoring mark-ups.

[38]When we exclude the share of women from the regression, see e.g. column (2), the estimate on the college share variable becomes insignificant. This is consistent with our interpretation because the large rise in college enrollment (the bulk of which is explained, again, by women) is likely to have taken place from the top of the unobserved ability distribution.

[39]Goldin and Katz (2000) report the returns to college computed through the decennial Census starting from 1940. To obtain a continuous time series, we interpolate linearly between successive decades.

6.1 Factor Shares

The one-to-one mapping between the change in the relative price and the rate of technical change may break down when the shares of capital in the consumption and investment goods producing sectors differ. In such a model, with competitive markets and free factor mobility, it is simple to establish that the change in the relative price consists of two components

$$\Delta p_t^{c^*} - \Delta p_t^{i^*} = \Delta q_t - \left(\alpha^c - \alpha^i\right) \Delta \kappa_t,$$

where α^c and α^i are the capital shares in the consumption and investment sectors, respectively, and $\Delta \kappa_t$ is the growth rate of the economy-wide capital-labor ratio.

We can assess the extent of the share-bias by constructing sector-specific capital shares and the capital-labor ratio. Define the investment goods sector as durable goods manufacturing and business services, which is dominated by software manufacturers, with the consumption goods sector consisting of the remaining industries. Such a break-down is not perfect, mostly because durable goods manufacturers produce at least some consumption goods. Nevertheless, classification errors do not affect the finding that the consumption goods sector is considerably more capital intensive than the investment goods sector. According to our calculations — based on data since 1948 when full-time equivalent worker data at the industry level are first available — $\alpha^c = 0.45$ and $\alpha^i = 0.26$. Since the capital-labor ratio was growing at about a 4.5 percent annual rate, our baseline measure of technical change underestimates actual growth by nearly 0.85 percentage point annually since 1948. Moreover, this number is larger in the second part of the sample, suggesting that the acceleration of the 1980's could be slightly larger. In Figure 1, we plot as a dashed line the bias-corrected series for technical change.

6.2 Mismeasurement

Our measure of investment-specific technical change is biased upward when quality improvement in consumption is neglected. Suppose NIPA consumption price indexes

p_t^c understate quality by a factor u_t^c so that $p_t^c = u_t^c p_t^{c^*}$. Using this relation with equation (3), we conclude that the change in the price of investment relative to consumption overestimates technical change when $\Delta u_t^c > 0$.

The similarity we discussed in section 2.6 between various consumption price indexes gives us some confidence that our measure is not seriously distorted. Nevertheless, it would be preferable to construct a constant-quality consumption price index using the sort of approach we adopt for measuring constant-quality investment. Unfortunately, the data for such an exercise are simply not available. Indeed, there are no studies documenting by how much the personal consumption expenditures deflator (PCE) neglects quality improvement over the period we consider. We can get some idea from Moulton (2001), who documents the expanding role of hedonic methods in the official statistics: currently, almost 20 percent of final expenditures is deflated through hedonic price indexes. Much of the adjustment is in durable consumption goods (e.g., PCs, apparel, audio and video equipment, refrigerators, and microwave ovens). Among services, only housing rents are adjusted for quality.

Although BEA has consistently upgraded its methods of accounting for quality improvement, most commentators express the view that quality adjustment for many goods is still insufficient (see, Wilcox and Shapiro 1996 and Lebow and Rudd 2001). It is tempting to conclude that the bias has increased over time due to increased expenditures on high-tech durables. But this would be incorrect because, as argued above, methods for accounting for quality have also improved. Moreover, a discussion about whether the bias is, say, zero or 1 percentage point is secondary in our application. The quality bias in investment goods that we correct for is so large as to swamp even the largest estimates of the quality bias in PCE.

6.3 Mark-ups

Finally, in our simple model we assumed that goods markets are competitive. The presence of mark-ups in the investment and in the consumption goods sectors would also change our key equation (3). Recall that we measure technical change in terms of growth rates, so constant mark-ups would leave our results unaffected.[40] Time-varying mark-ups do pose a problem since we would attribute changes in mark-ups to changes in the state of technology. In particular, slower-growing (or faster declining) mark-ups in the investment good sector would bias upward our measure of investment-specific technical change.

Our industry-level data enable us to get a feel for how mark-ups in the consumption and investment sectors have evolved.[41] Denote the non-competitive price as $\widetilde{p}_t$ so that $\widetilde{p}_t = (1 + \mu_t)p_t$, where p_t is the competitive price and μ_t is the mark-up. From the definition of profits, $\Pi_t = \widetilde{p}_t y_t - c_t$, where y_t is output and c_t is the cost of production. From the relation $p_t y_t = c_t$, it follows that $\mu_t = \pi_t/(1 - \pi_t)$ where π_t is the profit rate, i.e. $\pi_t = \Pi_t/(\widetilde{p}_t y_t)$, which can be calculated for the consumption and investment good sectors using our data.

Two conclusions emerge from these calculations. First, mark-ups have been falling in both sectors: in the investment (consumption) sector mark-ups decline from 23 (13) percent in the 1950s to 7 (8) percent in the early 1980s, and then they remain steady until 2000.[42] Although this suggests that the growth in our aggregate index of investment-specific technical change could be overestimated by 0.25 percentage point per year, quantitatively this bias is very small. Second, mark-ups in the investment goods sector are growing faster than mark-ups in the consumption goods sector since the 1980s. This bias leads to an underestimate of the recent technological acceleration.

[40] Different models of imperfect competition, such as the one Hobijn (2001) develops, do not necessarily lead to the same conclusion.

[41] We classify the consumption and investment goods sectors in the same manner as described in Section 6.1.

[42] Domowitz, Hubbard and Petersen (1986) estimate larger price-cost margins in the US (on the order of 26 percent in both sectors) between 1958-81. However, in a companion paper (Domowitz, Hubbard and Petersen, 1988) they modify their computation and essentially calculate profit rates, as we do (Table 5, page 64). This adjustment reduces their estimate by 10 percentage points on average, leading to estimates of mark-ups in line with our numbers.

7 Conclusion

The quantitative importance of productivity improvement in investment goods is a central issue in a number of macroeconomic debates (on rising wage inequality, the productivity slowdown and resurgence, and the dynamics of the stockmarket, just to cite a few). In this paper, we use a price-based approach to measure technical change at the asset, industry, and aggregate level in the US from 1947 to 2000. Whenever we faced a choice in constructing the data, we opted for the conservative alternative that understates the importance of quality improvement. Nevertheless, our aggregate and industry-level findings suggest that technical change in equipment and software in the postwar period has been large and was instrumental in the growth resurgence in the 1990s.

We show that the rate of technical change has accelerated in the past two decades. Most of the initial acceleration is due to a shift in investment toward computers, software, and communications equipment. However, later the growth rate of the leading edge technology accelerated for virtually every investment good and in every industry, demonstrating that information technology may cause generalized productivity improvements.

The fact that the productivity of new vintages advanced at about the same rate for every industry does not imply that the average practice did too, and indeed it did not. Certain industries kept up with the fast pace of technical change better than others, as demonstrated by our finding of a widening of the cross-sectional distribution of the technological gap. Perhaps surprisingly, the gap was largest in industries like communications in which investment has been robust. The explanation is simply that technical change in these industries has outpaced even the rapid pace of investment.

Why is there a subset of industries that exploit technological progress faster than others by investing heavily in new vintages of equipment and software? The first encouraging lead comes from Hobijn and Jovanovic (2001, Figure 8), who show that small firms outperformed large firms in the stock market from 1973 to 1982.[43] After that period, large firms outperformed small firms. One interpretation of this finding is that small firms first adopted information technologies, boosting their expected profits and their share prices. A decade later, large firms started to invest massively in computers, software, and communications equipment, regaining their dominant position. This interpretation matches the behavior of the technological gap for IPES (Figure 4), which increased quickly in the 1970s and leveled-off in the last two decades once large firms shifted investment to IPES from other equipment.[44]

Second, at the aggregate level, we confirm Nelson and Phelps' hypothesis that the speed of adoption of new technology is determined by the gap between the average and best practice, and by specific features of the workforce. In particular, we find aggregate evidence that younger, more able, and better-educated workers were the catalysts for adoption. Moreover, the increase in the college skill premium appears to reflect the premium to "adaptability" during periods of rapid technological progress and expanding technological gap, where the demand for adaptable labor was especially strong.

To conclude, although at this stage of our research we cannot identify precisely the distinctive features of those organizations that led the adoption of the new technologies in the postwar US economy, two promising candidates are the size of firms and the "adaptability" of the workforce.

[43] Mitchell (2001) develops a theoretical model consistent with this finding. Within a simple industry equilibrium model, he shows that the optimal scale of production is smaller when the rate of embodied technical change increases.

[44] It is also consistent with the fact that aggregate nominal expenditure shares in IPES show a remarkable acceleration from the early-1980's (Table 5.8, SCB).

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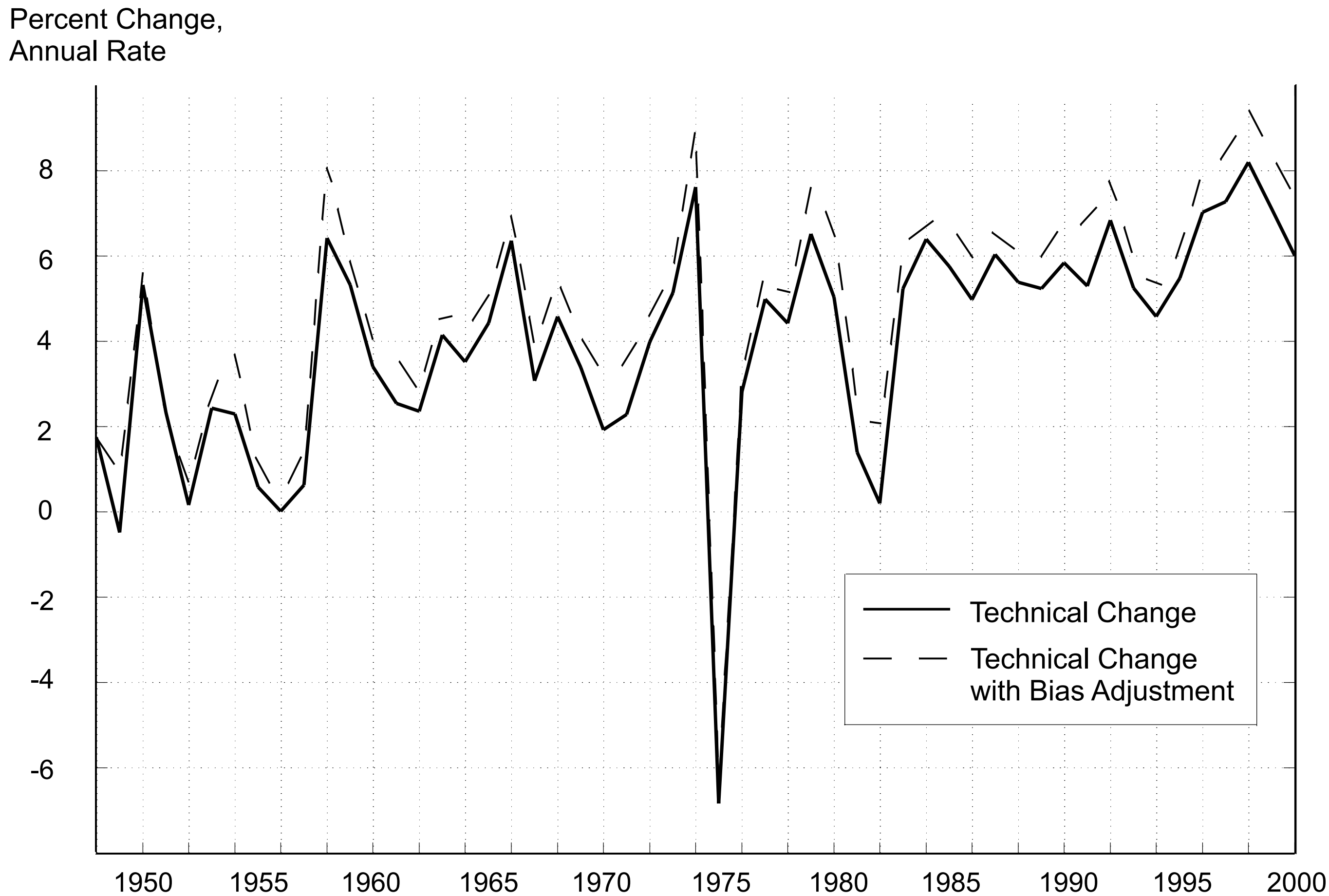

Figure 1: Price-Based Aggregate Measures of Investment-Specific Technical Change

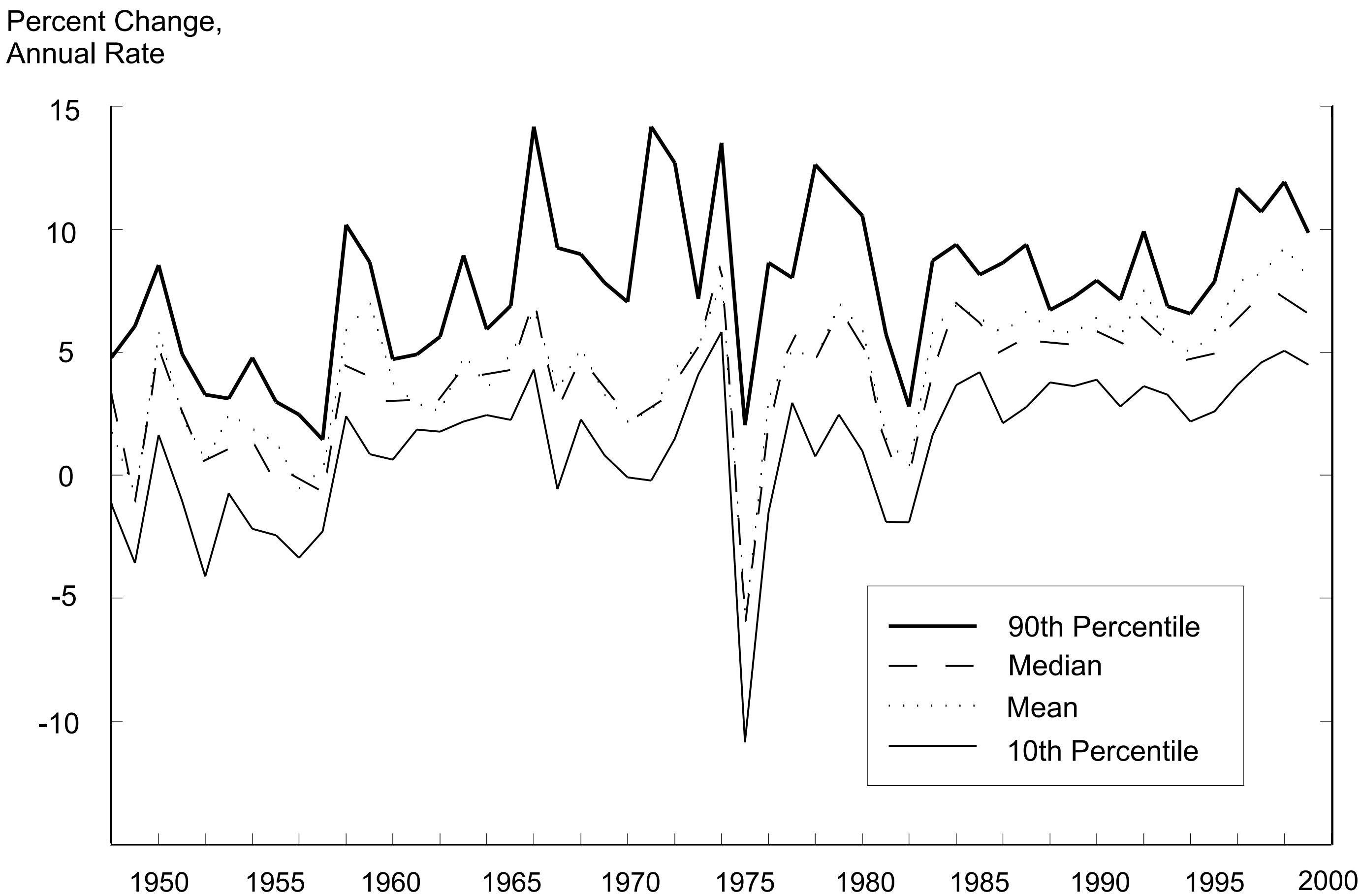

Figure 2: Distribution of Price-Based Measure of Investment-Specific Technical Change by 62 Industry Groups

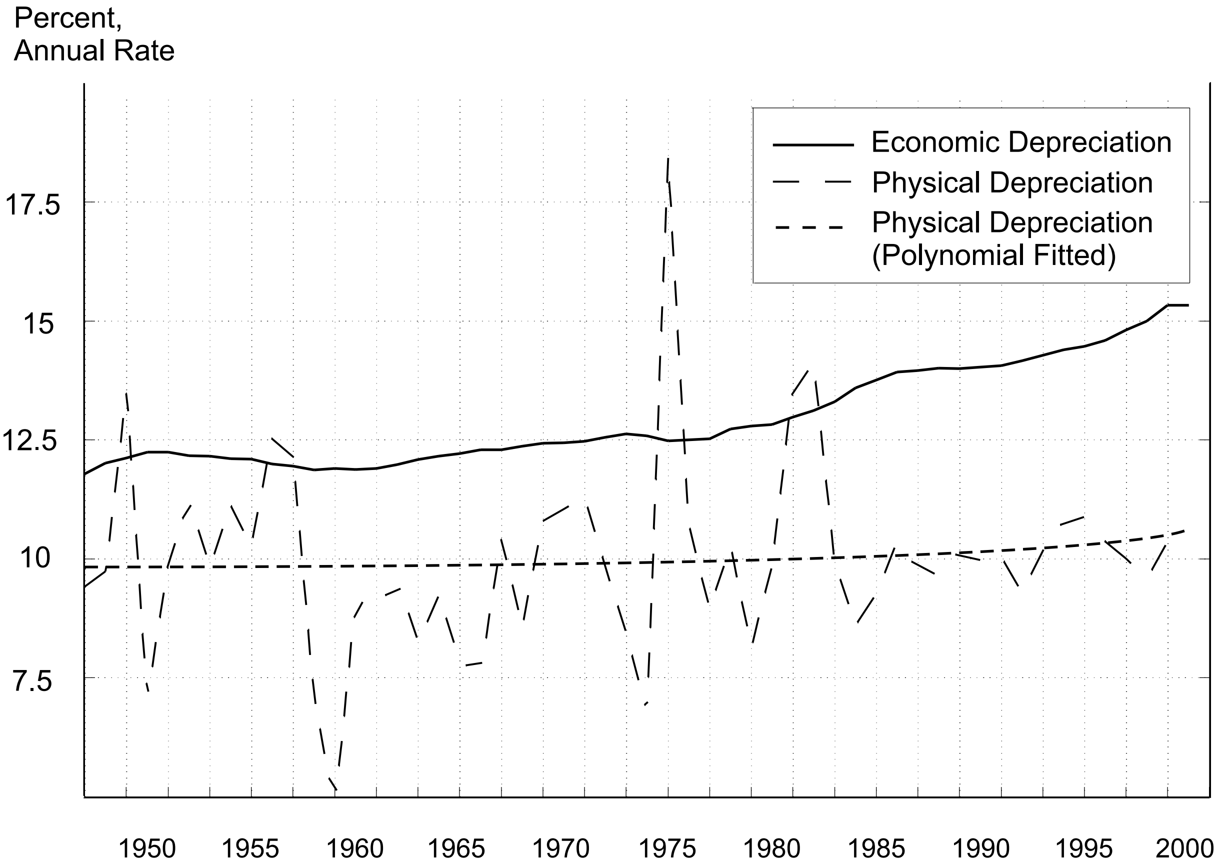

Figure 3: Economic and Physical Depreciation for Equipment and Software

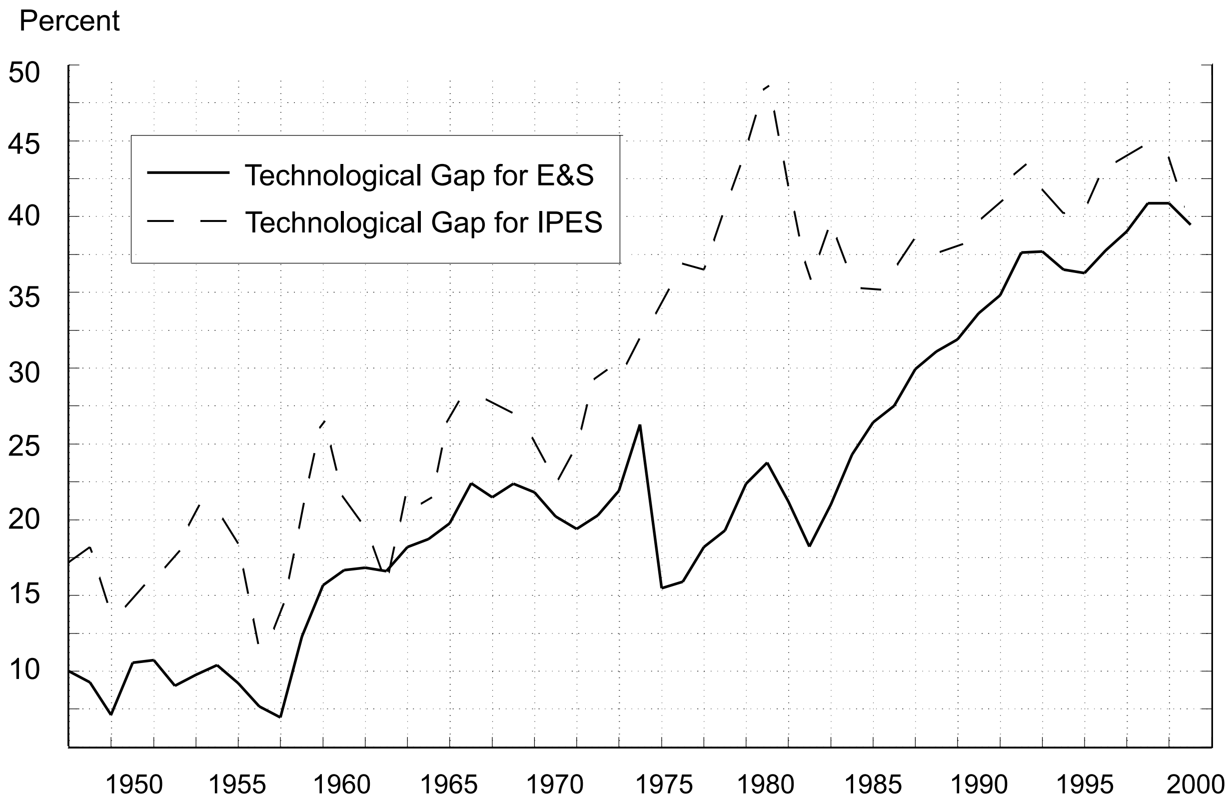

Figure 4: Technological Gap Between Productivity of New Vintages and Average Practice

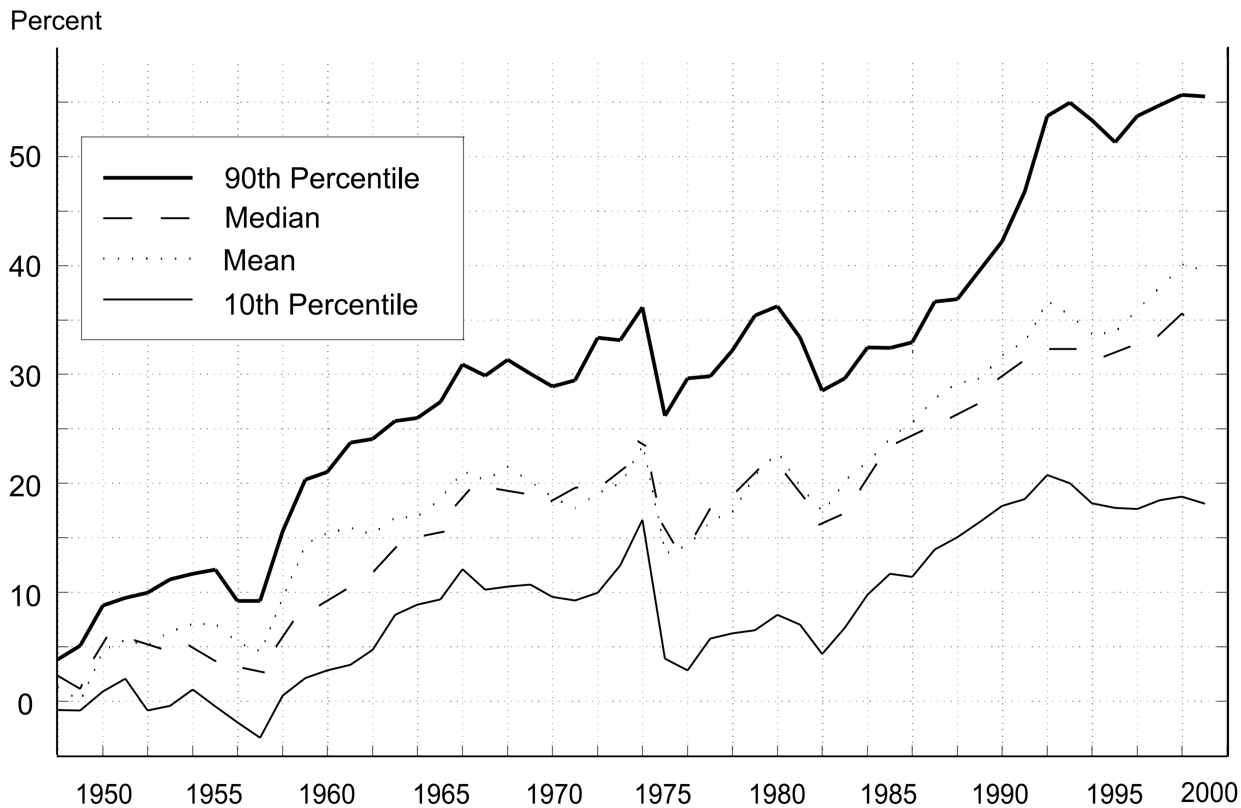

Figure 5: Distribution of Technological Gap Between Productivity of New Vintages and Average Practice for Equipment and Software by 62 Industry Groups

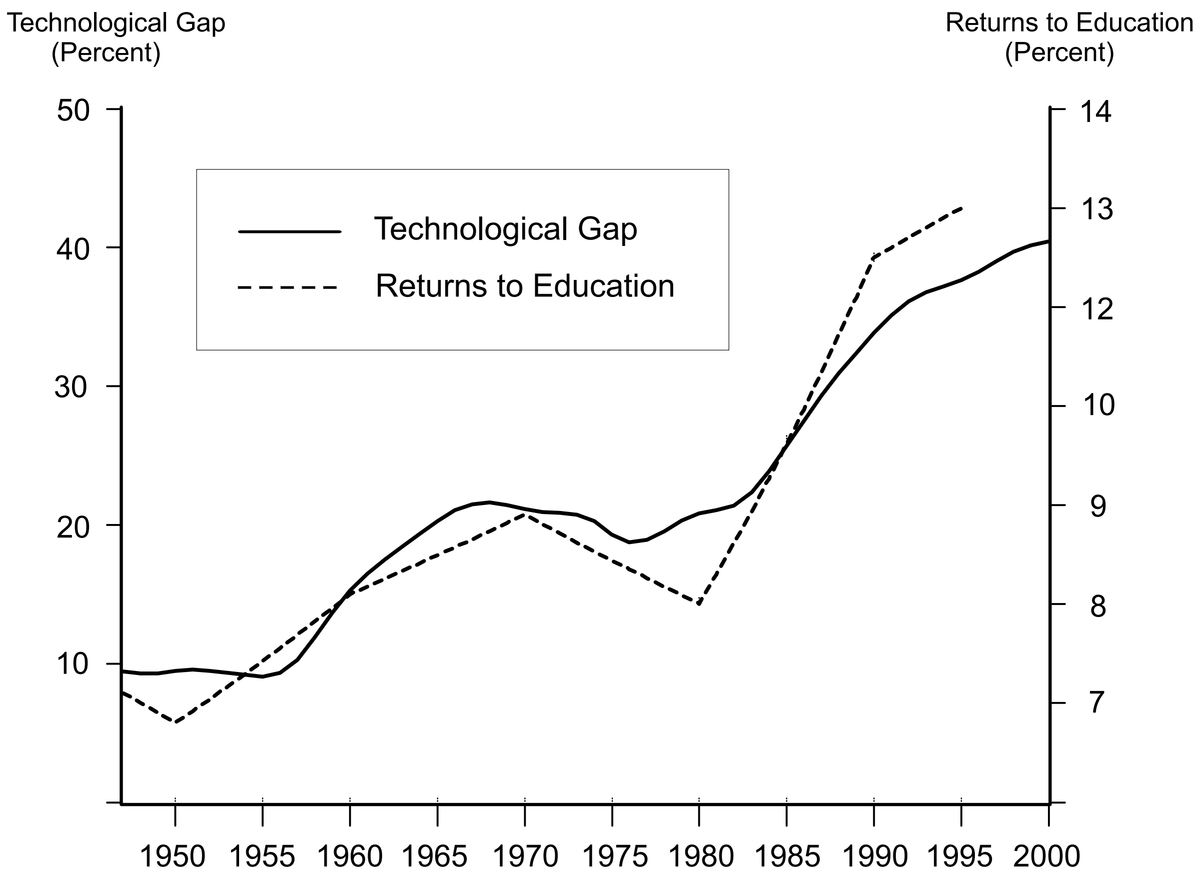

Figure 6: Returns to Education and Smoothed Technological Gap Between Productivity of New Vintages and Average Practice for Equipment and Software

Table 1: OLS Estimates of Quality-Bias in NIPA Price Indexes for Equipment and Software (1947-1983)

	Industrial Equipment						Transportation Equipment					Other Equipment								IPES	
Variable	Elec Tran (1)	Engn& Turbn (2)	Fabr Metl (3)	Gnrl Eqp (4)	Metl Mach (5)	Spcl Mach (6)	Air (7)	Auto (8)	Rail (9)	Ship& Boats (10)	Trck &Bus (11)	Agrc Mach (12)	Cnst Mach (13)	Elec Eqp (14)	Furn (15)	Mine &Oil (16)	Othr Eqp (17)	Srvc Mach (18)	Trctr (19)	Comm Eqp (20)	Inst& Photo (21)
Trend*100	-3.30	-6.06	-3.13	-1.08	—	-4.58	-15.0	-0.85	-0.82	-3.16	-3.65	—	-1.91	—	-0.91	-0.85	-1.37	-4.64	—	-6.65	-4.57
	(0.35)	(0.77)	(0.35)	(0.27)		(0.28)	(1.26)	(0.25)	(0.15)	(0.17)	(0.25)		(0.19)		(0.18)	(0.21)	(0.31)	(0.16)		(0.42)	(1.37)
$\log\left(p_t^{i_j}\right)$	1.40	1.48	1.23	0.76	0.72	0.99	2.37	0.84	0.86	1.51	1.15	1.71	0.95	1.23	0.60	0.73	1.10	1.22	1.25	1.68	-0.57
	(0.16)	(0.10)	(0.08)	(0.06)	(0.23)	(0.05)	(0.28)	(0.17)	(0.03)	(0.18)	(0.25)	(0.12)	(0.04)	(0.15)	(0.20)	(0.04)	(0.11)	(0.05)	(0.18)	(0.16)	(0.24)
$\log\left(p_{t-m}^{i_j}\right)$	-0.49	—	—	—	-0.74	—	—	0.42	—	-0.88	—	-0.69	—	—	0.42	—	—	—-	-0.55	—	1.36
	(0.19)				(0.24)			(0.19)		(0.21)		(0.13)			(0.20)				(0.20)		(0.56)
Δy_{t-n}	—	—	-0.01	-0.01	-0.01	—	—	—	—	—	—	—	-0.01	—	-0.01	-0.01	—	—	0.01	0.01	—
			(0.005)	(0.003)	(0.003)								(0.004)		(0.003)	(0.005)			(0.003)	(0.006)	
$\bar{R}^2$	0.87	0.77	0.93	0.98	0.99	0.91	0.89	0.79	0.99	0.99	0.91	0.99	0.99	0.95	0.99	0.98	0.86	0.96	0.98	0.91	0.77
	Estimates of Quality-Bias Using R&D Capital Stock (1957–83)																				
$\log\left(R\&D_t\right)$	-0.27	-0.30	-0.08	-0.05	-0.05	-0.04	-0.83	—	NA	NA	-0.30	—	NA	NA	NA	NA	NA	NA	NA	NA	-0.44
	(0.10)	(0.07)	(0.02)	(0.02)	(0.02)	(0.01)	(0.12)				(0.06)										(0.07)
$\log\left(p_t^{i_j}\right)$	0.87	1.17	0.91	0.73	0.86	0.96	1.11	0.45			0.90	1.45									-2.40
	(0.24)	(0.12)	(0.05)	(0.04)	(0.04)	(0.06)	(0.22)	(0.12)			(0.06)	(0.17)									(0.43)
$\log\left(p_{t-m}^{i_j}\right)$	—	—	—	—	—	—	—	0.72			—	-0.56									2.79
								(0.16)				(0.19)									(0.55)
Δy_{t-n}	—	-0.02	-0.01	-0.01	-0.01	—	—	—			—	—									—
		(0.008)	(0.003)	(0.003)	(0.005)																
$\bar{R}^2$	0.44	0.93	0.97	0.99	0.99	0.94	0.68	0.93			0.95	0.99									0.91

Each column contains estimates of a separate equation in which the dependent variable is $\log\left(p_t^{i_j^*}\right)$.

The order of the lags m and n is chosen to assure the best fit. In the three cases in which more than one lag was statistically significant, we report only the most precisely estimated lag to simplify the presentation.

Standard errors on coefficients are in parentheses.

Table 2: Price-Based Measure of Investment-Specific Technical Change by Asset (Percent Change, Annual Rate)

	1948–2000	1948–59	1960–69	1970–79	1980–89	1990–2000
EQUIPMENT AND SOFTWARE	4.0	2.3	3.6	3.6	4.6	6.3
IPES	9.7	4.5	7.3	11.7	9.4	10.6
Computers and peripheral equipment	23.5†	—	26.6	26.5	18.2	22.5
Prepackaged software	15.3†	—	15.7	18.1	15.8	9.9
Custom software	3.8†	—	4.0	4.4	3.6	2.6
Own-account software	0.2†	—	0.5	0.3	0.1	0.3
Communication equipment	8.7	9.6	5.1	7.3	8.5	12.9
Instruments, photocopy, and related equipment	5.6	1.7	3.4	13.5	5.0	5.4
Office and accounting equipment	2.4	0.0	2.1	5.3	3.1	2.4
INDUSTRIAL EQUIPMENT	2.3	1.9	2.8	1.3	2.1	3.6
Electrical transmission, distribution, and industrial apparatus	2.6	1.8	4.1	2.5	0.7	4.4
Engines and turbines	3.2	4.4	3.7	1.7	3.4	5.9
Fabricated metal products	2.7	2.8	3.1	1.2	4.4	4.7
General industrial equipment	1.6	0.4	1.8	2.2	1.3	2.6
Metalworking machinery	0.9	0.5	1.1	0.9	0.8	1.6
Special industry machinery	3.8	3.2	4.2	2.7	3.6	5.2
TRANSPORTATION EQUIPMENT	3.2	2.5	4.2	2.0	3.0	4.3
Aircraft	7.9	8.1	8.4	3.5	9.1	10.6
Autos	2.5	2.9	3.2	3.0	0.6	2.6
Railroad equipment	1.0	1.3	2.3	0.6	3.1	2.3
Ships and boats	2.1	1.5	2.6	0.3	3.0	3.4
Trucks, buses, and truck trailers	3.3	3.0	4.5	1.5	3.3	4.0
OTHER EQUIPMENT	1.7	1.5	1.9	0.5	2.0	2.5
Agricultural machinery	0.1	0.5	0.7	3.0	1.6	0.9
Construction machinery	1.3	0.5	1.6	0.5	1.6	2.6
Electrical equipment	2.0	1.4	2.7	1.1	2.4	3.0
Furniture and fixtures	1.1	0.9	1.4	0.6	0.8	2.0
Mining and oilfield machinery	1.4	0.5	1.6	0.5	2.4	2.1
Other equipment	2.4	3.4	2.0	2.1	1.9	2.3
Service industry machinery	4.9	5.3	6.0	3.6	4.6	5.1
Tractors	0.3	2.2	0.9	0.1	2.0	1.8

Each entry is the annual average during the period. The price-based measure of investment-specific technical change is calculated as the difference between the growth rate of constant-quality consumption and the growth rate of the quality-adjusted price of asset j.

The † denotes the annual average is for the period 1960-2000.

Table 3: Price-Based Measure of Investment-Specific Technical Change (Percent Change, Annual Rate) and Nominal Equipment and Software Investment Shares by Major Industry

	1948–2000		1948–59		1960–69		1970–79		1980–89		1990–2000	
	Technical Change	Nominal Share	Technical Change	Nominal Share	Technical Change	Nominal Share	Technical Change	Nominal Share	Technical Change	Nominal Share	Technical Change	Nominal Share
Agriculture, Forestry and Fishing	1.1	8.0	0.8	12.4	1.1	8.7	-0.8	8.4	2.3	4.4	2.4	4.3
Mining, Oil and Gas Extraction	2.4	3.3	0.9	3.0	2.4	3.2	1.5	3.9	3.5	4.0	4.4	2.2
Construction	2.2	3.7	1.1	5.2	2.4	4.7	1.0	3.7	2.7	2.0	4.5	2.4
Durable Goods Manufacturing	3.5	13.9	1.3	14.8	3.2	15.5	3.9	14.5	4.1	12.9	5.7	11.5
Nondurable Goods Manufacturing	3.9	11.9	2.4	12.9	3.9	12.7	4.0	12.1	4.1	10.7	5.6	10.8
Transporation and Utilities	4.0	15.6	2.3	18.4	4.9	16.2	2.2	15.5	4.6	14.3	6.7	12.3
Communications	7.7	7.9	7.6	6.2	5.2	8.6	7.3	8.6	8.1	8.2	10.9	8.5
Wholesale Trade	5.5	5.8	2.6	3.5	4.8	4.5	6.0	5.4	6.4	8.0	8.8	8.6
Retail Trade	4.3	5.7	3.3	6.7	4.3	5.6	3.8	5.0	4.9	5.6	5.9	5.4
Finance, Insurance, and Real Estate	5.6	13.1	3.4	8.8	4.8	9.7	7.0	11.7	5.8	17.7	8.0	19.5
Other Services	5.0	11.1	2.9	8.1	4.6	10.6	5.3	11.1	6.2	12.1	6.8	14.5

Each entry is the annual average during the period. The price-based measure of investment-specific technical change is calculated as the difference between the growth rate of constant-quality consumption and the growth rate of the quality-adjusted price of asset j.

Table 4: Quality-Adjusted and BEA Capital Stocks (Percent Change, Annual Rate)

	1948–2000	1948–59	1960–69	1970–79	1980–89	1990–2000
1. k_e^*	8.8	9.1	8.9	8.7	7.5	10.0
2. k_e^{BEA}	5.8	5.6	5.9	6.1	4.6	6.8
Difference (1-2)	3.0	3.5	3.0	2.6	2.9	3.2
3. k_{ipes}^*	16.3	13.7	16.5	17.9	17.2	16.3
4. k_{ipes}^{BEA}	12.3	8.6	13.2	13.7	13.2	13.3
Difference (3-4)	4.0	5.1	3.3	4.2	4.0	3.0

Table 5: Statistical Growth Accounting (1948–1999)

	Real GDP Calculated Using Constant-Quality Consumption Price Index						Real GDP Calculated Using Constant-Quality Consumption and Investment Price Indexes					
	1948–99	1948–59	1960–69	1970–79	1980–89	1990–99	1948–99	1948–59	1960–69	1970–79	1980–89	1990–99
Real GDP (Percent Change, Annual Rate)	3.72	3.68	4.34	3.64	3.39	3.53	4.01	3.69	4.82	3.89	3.60	4.15
Contribution of Capital ($k^* = Q\tilde{k}$)	53.6	41.1	48.7	59.7	60.2	64.2	49.7	41.0	43.8	55.8	56.8	54.7
Quality of Capital (Q)	21.1	18.2	18.1	16.9	24.1	31.0	19.6	18.1	16.3	15.8	22.7	26.4
IPES Capital (Q_{IPES})	6.0	1.4	2.7	6.2	9.0	12.4	5.6	1.4	2.4	5.8	8.5	10.6
Other Capital (Q_{Other})	15.1	16.8	15.4	10.7	15.1	18.6	14.0	16.7	13.9	10.0	14.2	15.8
Quantity of Capital ($\tilde{k}$)	32.5	22.9	30.6	42.8	36.1	33.2	30.1	22.8	27.5	40.0	34.1	28.3
IPES Capital ($\tilde{k}_{IPES}$)	5.5	2.6	3.9	4.9	6.0	4.9	5.1	2.6	3.5	4.6	5.7	4.2
Other Capital ($\tilde{k}_{Other}$)	27.0	20.3	26.7	37.9	30.1	28.3	25.0	20.2	24.0	35.4	28.4	24.1
Contribution of Labor ($l = hn$)	32.3	20.0	29.0	34.2	41.3	41.9	29.9	20.0	26.1	32.0	38.9	35.7
Quality of Labor (h)	10.4	17.1	13.2	15.6	6.2	7.4	9.6	17.0	11.9	14.6	5.8	6.3
Quantity of Labor (n)	21.9	2.9	15.8	18.6	35.1	34.5	20.3	2.9	14.2	17.4	33.1	29.4
Contribution of TFP (z)	14.1	38.9	22.4	6.1	-1.5	-6.1	20.4	39.0	30.1	12.2	4.0	9.6

The contribution of each input is the ratio of the share-weighted real growth rate of the input and real GDP growth. The aggregate share of labor (capital) is 0.64 (0.36) over the sample period.

Table 6: Decomposition of Increase in Growth Rate of Labor Productivity in 1995-1999

		Ravn-Uhlig (λ = 6.25)		Hodrick-Prescott (λ = 100)	
	Contribution	Cycle	Trend	Cycle	Trend
Increase in Growth Rate of Labor Productivity		31.5	68.5	88.9	11.1
Contribution of Capital	42.3	17.0	25.3	43.3	-10.0
Quality of Capital	66.1	9.3	56.8	30.8	35.3
IPES Capital	28.6	5.8	22.8	20.4	8.2
Other Capital	37.5	3.5	34.0	10.4	27.1
Quantity of Capital	-23.8	7.7	-31.5	12.5	-36.6
IPES Capital	-4.0	5.1	-9.0	13.6	-17.5
Other Capital	-19.9	2.6	-22.5	-0.9	-18.8
Contribution of Labor Quality	-29.7	-12.4	-17.3	-29.4	-0.3
Contribution of TFP	87.5	27.0	60.5	75.0	12.5

The growth rate of labor productivity increased from an annual rate of 1.77 percent in 1973–94 to an annual rate of 2.64 percent in 1995–99. The cyclical component of the increase is extracted from each series using the Hodrick-Prescott filter. We use filtering parameters suggested for annual data by Ravn and Uhlig and Hodrick and Prescott. The contribution of each input is the ratio between the share-weighted real growth rate of the input and the growth rate of labor productivity. The aggregate share of labor (capital) is 0.64 (0.36) over the sample period.

Table 7: Technological Gap Between Productivity of New Vintages and Average Practice by Major Industry

	1948–2000	1948–59	1960–69	1970–79	1980–89	1990–2000
Agriculture, Forestry, and Fishing	5.1	1.5	6.7	-0.8	6.4	13.4
Mining, Oil and Gas Extraction	11.8	2.7	9.7	7.5	14.2	29.5
Construction	9.4	3.1	9.8	6.4	10.3	20.3
Durable Goods Manufacturing	17.7	4.2	12.9	17.3	24.5	35.5
Nondurable Goods Manufacturing	22.8	8.8	21.9	24.0	27.2	37.9
Transportation and Utilities	28.3	5.6	32.0	28.0	30.1	55.6
Communications	41.0	24.0	31.9	27.4	56.8	73.4
Wholesale Trade	18.3	6.9	15.4	18.8	23.0	32.0
Retail Trade	18.5	9.2	20.6	17.7	21.3	27.3
Finance, Insurance, and Real Estate	20.0	8.4	17.9	24.2	23.3	30.9
Other Services	18.2	5.9	16.1	21.1	24.7	28.0

Table 8: OLS Estimates of Nelson-Phelps Adoption Equation (1948–99)

Variable	(1)	(2)	(3)	(4)	(5)
$\log(\Gamma_{t-1})$	0.84	0.84	0.72	0.66	0.67
	(0.05)	(0.05)	(0.12)	(0.12)	(0.14)
Share of Young Workers	—	0.46	0.67	2.75	2.83
(ages 16-24)		(0.85)	(0.87)	(1.23)	(1.35)
Share of College Graduates	—	—	0.93	10.9	11.0
			(0.84)	(4.44)	(4.49)
Share of Female Workers	—	—	—	-10.5	-10.4
				(4.57)	(4.62)
Share of Self-employed	—	—	—	—	0.27
					(1.82)
Durbin-Watson	1.59	1.62	1.53	1.49	1.50
$\bar{R}^2$	0.85	0.85	0.85	0.87	0.87

Each column contains estimates of a separate equation in which the dependent variable is $\log(\Delta Q_t)$.

Standard errors on coefficients are in parentheses.