Equipment-Embodied Technical Change in the US (1947–2000): Measurement and Applications*

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Abstract

By extrapolating the quality-bias in the official price indexes measured by Gordon (1990), we construct quality-adjusted price indexes by type of equipment from 1947-2000, and use them to measure embodied technical change at the aggregate and industry level. At the aggregate level, we find that (1) equipment embodied technical change grew at 4 percent per year on average in the postwar period and accelerated to more than 6 percent in the 1990s, and (2) the technological gap between the frontier technology and the average machine in the economy has doubled since the 1970s. The aggregate calculations mask great variation in the rates of embodied technical progress across industries, ranging from about 1 percent in agriculture to more than 7 percent in communications. The technological gap increased substantially in all industries and displays substantial inter-industry variation. We find that embodied technical change, not TFP, is the driving force of growth outside of durable goods manufacturing.

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1 Introduction

In the neoclassical growth model, factor accumulation drives growth only in the short-run since diminishing returns implies that exogenous technological progress is the only source of long-run growth. In Solow (1957) technological change was disembodied from all productive inputs and, as such, was easily measured as a residual. This last observation was enormously influential in the empirical literature on growth accounting, as it paved the way for a very simple decomposition of the growth in income per capita into capital deepening and "total factor productivity". Standard growth accounting exercises in the 1960s and early 1970s led systematically to the conclusion that disembodied technical change was a key determinant of economic growth.

The representation of technology as purely disembodied is, in the words of Solow (1960) himself, "as if all technical progress were a way of improving the organization and operation of inputs without reference to the nature of the inputs themselves. The striking assumption is that old and new capital equipment participate equally in technical progress." By definition, the level of disembodied technology advances in the economy without any need to invest in the new vintages of capital goods. The experience of developed economies over the last three decades suggests a very different view of technical change: most of technological improvements that we have witnessed are *embodied* in new types of investment (and consumption) goods. Perhaps the most profound advances have been in the field of microelectronics and are related to the progress of semiconductors. Key electronic components are now incorporated into a large array of goods, resulting in quality and efficiency improvements which were once unimaginable. It is only by investing in new vintages of equipment that firms can reap the productive benefits of such quality improvements.

This recent wave of embodied technological progress has a central role in current macroeconomic theories designed to explain some of the most important events of the last thirty years: the productivity slowdown of the 1980s, the stock market boom, the rise in wage inequality, and the productivity surge of the 1990s.

In the wake of a technological revolution, labor productivity may slow down initially because firms spend resources on implementing the new technology, on making it compatible with the old capital, and on training workers to use the new equipment (Hornstein and Krusell, 1996, Greenwood and Yorukoglu, 1997). Through a similar mechanism, profound technological advances may impact on the stock market. Greenwood and Jovanovic (1999) and Hobijn and Jovanovic (2000) argue that drastic innovations such as the computer can induce the stock market to fall temporarily because large incumbent firms, which are likely to make up for the bulk of the stock market value, find it extremely costly to adapt production to the new technological paradigm. It is only when newly created firms — whose capital fully embodies the new innovations — start issuing equity that the stock market recovers and comes to reflect the full profitability potential of the new technologies. Moreover, wage inequality may rise during periods of rapid technical change.[1] An explicit mechanism based on embodied technical change is provided by Krusell, Ohanian, Rios-Rull, and Violante (2000): when equipment and skilled labor are complementary in production, an acceleration in equipment investment due to quality improvement (and rapidly falling relative price) raises the demand for skilled labor and the skill premium. Finally, a number of important empirical studies have analyzed both at the aggregate and at the industry level the extraordinary productivity performance of the US economy in the period 1995-1999 and have concluded that the core of productivity growth is due to investment in information technologies (Jorgenson and Stiroh, 2000a, 2000b, and Oliner and Sichel, 1994).[2]

An additional reason why embodied technological change has an important role in economics is the design of public policy. The desirability of investment subsidies, such as investment tax credits and R&D tax credits, depends on the relative importance of embodied and disembodied technical change. For example, if capital-embodied quality improvements are large and, at the same time, spillovers exist across firms or industries in the efficient use of new technologies (e.g., "social learning effects"), then certain policies can be welfare improving. In the labor market, when skills have a technology-specific component, rapid technical progress makes skills obsolete. Skill obsolescence may reduce the market value of workers so much

[1]See Acemoglu (2000) and Aghion (2001) for two surveys on the nexus between technological change and the labor market.

[2]Other explanations have been proposed for each of these phenomenon. Baily and Gordon (1988) argue that the productivity slowdown cannot be explained by technology. DiNardo, Fortin and Lemieux (1996) emphasize the importance of changes in institutions for the rise in wage inequality. Gordon (2000) attributes the recent productivity surge of the late 1990s essentially to cyclical factors. Finally, the oil shock, monetary policy and "irrational investors' behavior" are often cited as alternative explanations of the recent stock market dynamics.

that they are induced to quit the labor force. Murphy and Topel (1997) argue that this phenomenon is empirically relevant for explaining the rise in nonparticipation rates of prime-aged males in the US. This finding may justify government-sponsored training programs targeted to certain categories of workers.

Ultimately, whether embodied technical change is an engine of growth and a source of interesting macroeconomic dynamics is a quantitative question. The answer depends crucially on reliable and accurate measures of constant-quality price indexes for capital goods, in particular high-tech equipment.[3] Gordon (1990) provides the first systematic measurement of quality-adjusted prices for a large number of different types of producers' durable equipment. Hulten (1992) and Greenwood, Hercowitz, and Krusell (1997) incorporated Gordon's estimates of constant-quality price indexes into a Solow (1960) vintage capital model in order to measure capital-embodied technical change in the aggregate economy. Because Gordon's data cover the postwar period until 1983, Hulten's analysis is limited to that period, while Greenwood, Hercowitz and Krusell extend the aggregate series to 1992 using a conjectured constant adjustment factor on the official price-index.

Gordon's work has also been enormously influential on the procedures adopted by the US Bureau of Economic Analysis (BEA) to improve the measurement of quality: investments in key high-tech goods such as computers, pre-packaged software and digital switching equipment are now deflated through constant-quality price indexes computed with best-practice hedonic techniques. However, as microelectronic components become cheaper and more flexible, almost every investment good embeds information technology at least to some extent. Thus, important measurement issues for new types of goods emerge continuously in the data and suggest that a gap still exists between the official price indexes and ones that would fully adjust for quality.

In this paper we attempt to fill this gap using a "second-best" approach:[4] starting from Gordon's quality-adjusted price indexes for the period 1947-1983, we estimate the quality bias implicit in the official series for that period and then, using the current NIPA official price indexes we extrapolate the quality bias throughout 1984-2000. This allows us to construct constant-

[3]For an alternative approach to measuring investment-specific technical change based on production function estimation, see Bakh and Gort (1993), Gort, Bahk and Wall (1993) and, more recently, Sakellaris and Wilson (2000).

[4]The "first-best" approach, which would replicate Gordon's work for every type of equipment, is a monumental effort that the BEA is slowly implementing.

quality price indexes for all of the main assets in NIPA equipment and software (E&S) (except those for which the quality adjustment is clearly already included in the official prices, like for computers). The ratio of each price index to a consumption price index allows us to measure the speed of technological change embodied in the assets. Excluding computers and software, for which the official price series seems to adequately capture quality-improvement, we find that the largest quality improvements occurred in communications equipment (8.7 percent per year), aircraft (7.9 percent per year), and instruments (5.6 percent per year).

We use these asset-specific price indexes to build an aggregate index of equipment-embodied technical change. We estimate that this index has grown at average annual rate of 4 percent per year in the postwar period, with a sharp acceleration in the 1980s that led to an yearly rate over 6.3 percent in the 1990s. By using our estimate of asset-specific quality improvements, we can filter out the obsolescence component from the official NIPA economic depreciation rates in the construction of the capital stock series. In particular, we show that almost the entire rise in the NIPA economic depreciation rate for equipment is attributable to obsolescence.

Using these corrected depreciation rates, we construct the aggregate capital stock and perform a "statistical" growth accounting exercise. Our major finding is that quality improvements in capital explain between 19.5 percent and 21 percent (according to whether output is quality-adjusted) of output growth in the US from 1948-1999, with quality improvements in IT alone explaining 12 percent of the growth in the last decade. Moreover, the "quantity" of capital (i.e., the quantity of capital in consumption units) accounts for a further 30 percent from 1948-1999. Once we embed this growth accounting exercise into a structural equilibrium model where capital accumulation can be explained through the underlying sources of growth (embodied in capital and labor, and disembodied), we compute that about 60 percent of labor productivity growth from 1948-1999 is attributable to capital-embodied quality improvements.

Following Hulten (1992), we also produce estimates of the technological gap embodied in equipment between the leading edge machine and the average practice in the economy: the key finding is that this gap increased steadily in the 1980s and 1990s from 20 percent in 1970 to almost 40 percent in 2000.

The rest of the paper is organized as follows: section 2 surveys the theoretical foundations of the price-based measurement of embodied technical change and develops a simple input-output model that motivates our methodology for the industry-level data. Section 3 outlines the procedure we used to construct our constant-quality price indexes for each asset category. Section 4 contains the results for the aggregate economy. Section 5 outlines our main findings with the industry-level data. Section 6 concludes.

2 Measuring Embodied Technical Change with Prices

In this section, we develop a simple theoretical framework in which quality-adjusted relative prices can be used to measure embodied technical change. In doing so, we revisit some existing results in the literature and adopt a balanced perspective on the so-called "embodiment controversy." In the final part of the section, we motivate our industry-level analysis with an input-output model and describe the assumptions needed for relative prices to measure sector-specific rates of embodied technical change.

The starting point of the price-based measurement of embodied technical change is the observation by Jorgenson (1966) that nominal investment is invariant to the units in which the goods are measured. Define i_t as investment measured in units like the number of machines and i_t^* as investment in efficiency units or, likewise, in constant-quality units. Let q_t be the quality index of an investment good produced at time t. Then the following relationships hold

$$p_t^i i_t = p_t^{i^*} i_t^* \Rightarrow \frac{1}{q_t} = \frac{p_t^{i^*}}{p_t^i},$$

where p_t^i is the unit-value price index and $p_t^{i^*}$ is the quality-adjusted price index. In this formulation, the quality index can be measured from the relative price $p_t^i/p_t^{i^*}$.

Quality-adjusted price indexes can be constructed using hedonic methods: a regression model relates observed price changes of a basket of goods to changes in the characteristics of the goods. The hedonic price index is constructed from the fitted relationship by measuring price changes holding constant quality.[5] The BEA has consistently upgraded its methods for account-

[5]The applied literature on hedonic price indexes is vast. For applications to computer prices, see for example Berndt and Griliches (1993) and Berndt, Griliches and Rappaport (1995).

ing for quality improvement in equipment. For example, BEA introduced hedonic-based quality-adjusted price indexes for computers and peripherals in 1985. Recently, hedonic techniques were introduced for pre-packaged software and some types of communications equipment (e.g., digital telephone switches).[6] Even before 1985 BEA tried to measure quality change in a number of ways using, for example, "matched-model" methods.[7]

Although many researchers have expressed the view that quality adjustment for many goods is still insufficient (see, in particular, Gordon, 1990), essentially all price indexes for equipment goods are, to at least some extent, quality-adjusted. The BEA makes no attempt to measure unit values. Hence, the unit-value index we introduced, p_t^i, is unavailable as data. This presents an obvious problem that is typically neglected by researchers: how can embodied technical change be measured using the price indexes that are available?[8] Fortunately, we can solve this problem using a simple theoretical model.

2.1 A One-Sector Model

Building on the work by Solow (1960), Greenwood-Hercowitz and Krusell (1997) (hereafter GHK) and Hercowitz (1998) propose the following general equilibrium one-sector aggregate model of the economy:

$$\begin{aligned} c_t + i_t &= z_t F(k_t, l_t) \\ i_t^* &= q_t i_t \\ k_{t+1} &= (1-\delta)k_t + i_t^*. \end{aligned}$$

The first equation is the resource constraint: investment i_t and consumption c_t are produced by a constant returns to scale (CRS) technology $F(\cdot)$ using

[6] Moulton (2001) documents the expanding role of hedonic methods in the official statistics: currently, 18 percent of final expenditures is deflated through hedonic price indexes. Much of the adjustment is in durable consumption goods (e.g., PC's, apparel, audio and video equipment, refrigerators, and microwave ovens). Among services, only housing rents are adjusted for quality.

[7] 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 during 1994–98.

[8] Notice that even the BEA considers this a serious problem. Landefeld and Grimm (2000) write: "one of the principle obstacles to estimating the impact of hedonic price indexes...is the lack of traditionally measured price indexes." (p. 20).

capital k_t and labor l_t services. Investment and consumption are perfect substitutes in output. The index of total factor productivity (TFP) is z_t. Notice the difference between i_t and i_t^*: the former is investment in consumption units and the latter is investment in efficiency units. The index q_t measures the quality (i.e., the efficiency units) of each unit of investment of vintage t. In this set-up, $p_t^c = p_t^i$. It follows immediately that

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

where Δ denotes the growth rate. Thus the rate of embodied quality improvement can be measured from the price of quality-adjusted investment relative to consumption.

In their study, GHK side with Solow (1960) instead of Jorgenson (1966) in the debate about whether the output of investment should be quality-adjusted. Following Solow, GHK and Hercowitz (1998) argue that an unfortunate consequence follows from expressing the resource constraint in quality-adjusted terms, as in rewriting the above as $c_t + i_t^* = z_t F(k_t, l_t)$: the ratio that is supposed to track quality improvement $p_t^c/p_t^{i^*}$ would be a constant, leaving no role for embodied technical change to affect growth. Given that the ratio $p_t^c/p_t^{i^*}$ increases sharply in the data, GHK and Hercowitz (1998) dismiss Jorgenson's approach as empirically untenable.

However, Jorgenson (1966) uses a multi-sectoral model of the economy that is more general than the model considered by GHK. Consider a competitive two-sector model (one sector producing consumption goods c_t and the other efficiency units of investment goods i_t^*) with different rates of disembodied technical change (z_t^c, z_t^i) and no embodied technical change: the change in the relative price $p_t^c/p_t^{i^*}$ will mirror the change in the ratio z_t^i/z_t^c. Hence, the observed increase in $p_t^c/p_t^{i^*}$ can be explained by a two-sector model with different rates of disembodied technical change.[9] Embodied technical change is unnecessary which begs the question: is embodied technical change is irrelevant?

[9]Technically, the two-sector model has to be "non-joint" and perfect aggregation impossible.

2.2 A Two-Sector Model

2.2.1 Identification of technical change

To answer to this question, consider an economy with two sectors, one producing investment goods i_t and the other producing consumption goods c_t. Each good is produced using a strictly concave, CRS production function with capital and labor. For simplicity, we specialize our analysis to the Cobb-Douglas case, but our main conclusions do not depend on this assumption:

$$\begin{aligned} c_t &= z_t^c k_{ct}^{\alpha} l_{ct}^{1-\alpha}, \\ i_t &= z_t^i k_{it}^{\beta} l_{it}^{1-\beta}. \end{aligned} \tag{1}$$

The indexes z_t^i and z_t^c are the sector-specific levels of disembodied productive efficiency. Investment in efficiency units is $i_t^* = q_t i_t$. The pair (k_{ct}, k_{it}) represents the allocations of efficiency units of capital in each of the two sectors, so that market clearing requires $k_{ct} + k_{it} = k_t$. The law of motion for capital is unchanged: $k_{t+1} = (1-\delta)k_t + i_t^*$. We assume perfect mobility of factors across sectors and competitive final goods and inputs markets. In equilibrium, the profit maximizing choices of capital and labor are

$$\begin{aligned} w_t &= p_t^i z_t^i (1-\beta) k_{it}^{\beta} l_{it}^{-\beta} = p_t^c z_t^c (1-\alpha) k_{ct}^{\alpha} l_{ct}^{-\alpha} \\ r_t + \delta &= p_t^i z_t^i \beta k_{it}^{\beta-1} l_{it}^{1-\beta} = p_t^c z_t^c \alpha k_{ct}^{\alpha-1} l_{ct}^{1-\alpha} \end{aligned} \tag{2}$$

which can be rearranged to give:

$$\frac{w_t}{r_t + \delta} = \frac{1-\beta}{\beta} \left(\frac{k_{it}}{l_{it}} \right) = \frac{1-\alpha}{\alpha} \left(\frac{k_{ct}}{l_{ct}} \right).$$

Let κ denote the capital-labor ratio, then the equation above yields

$$\kappa_{ct} = \kappa_{it} \frac{\alpha (1-\beta)}{\beta (1-\alpha)}.$$

From either of the two equations in (2), we obtain

$$\frac{p_t^c}{p_t^i} = \frac{z_t^i}{z_t^c} \kappa_{it}^{(\beta-\alpha)} \left(\frac{1-\beta}{1-\alpha} \right)^{1-\alpha} \left(\frac{\beta}{\alpha} \right)^{\alpha}.$$

Hence, the change in the GHK relative price equals

$$\Delta p_t^c - \Delta p_t^{i^*} = \Delta q_t + \left(\Delta z_t^i - \Delta z_t^c\right) + (\beta - \alpha)\,\Delta \kappa_{it}. \tag{3}$$

In this two-sector model, there is no longer a one-to-one mapping between the change in the relative price and the rate of embodied technical change, unless $\Delta z_t^i = \Delta z_t^c$ and $\beta = \alpha$. Abstracting for the moment from the possibility that sectoral shares differ, notice that we can measure z_t^c residually from the consumption sector data, but not z_t^i, as data are only available for $i_t^* = i_t^N / p_t^{i^*}$, where i_t^N is "nominal" investment. Alternatively, it is clear from (1) that if we multiply both sides of the resource constraint of the investment good sector by q_t and we use i_t^* as the (now observable) output of the sector, then residually we can measure at most $(\Delta q_t + \Delta z_t^i)$. In general, in a two-sector model Δq_t and Δz_t^i cannot be identified separately through relative price data.[10] This lack of identification is the core of the embodiment controversy.

2.2.2 The embodiment controversy

Two polar extremes have been charted to explain the sources of US economic growth. According to one approach, disembodied technical change proceeds at different rates in different industries. This difference accounts for the observed change in the relative price of capital (see, e.g., Jorgenson and Stiroh 2000a, 2000b).[11] According to the alternative approach, the investment-specific component of productivity is equal to the embodied component (Hornstein and Krusell 1996). Assuming that disembodied technical change is sector-neutral, embodied technical change can be measured using the relative price. One reason why the latter approach is natural in a two sector model can be seen by omitting the term z_t from the production functions above and rewriting the law of motion for capital as in Hall (1968)

$$k_t = z_t \sum_{\tau=0}^{t} (1-\delta)^{\tau} q_{t-\tau} i_{t-\tau}$$

[10] This result was proved in an elegant way by Hall (1968), who also explained that this is because q_t and z_t^i enter multiplicatively. With more general functional forms it might be possible to disentangle the two components.

[11] In these two studies the authors do not infer technical change using price data. Instead, they attribute technical change to the residual from an estimated Cobb-Douglas production function.

and the aggregate constraint for labor as $l_t = z_t n_t$ where n_t is "raw labor". The factor neutrality of disembodied technical change implies sector neutrality given CRS.

It is important to reiterate that when it comes to the data both the relative price and the "Solow residual" from the econometric estimation of production functions measure *investment-specific* technical change. However, for a number of reasons we prefer to argue that changes in the relative price measure embodied technical change. First, as we pointed out in the introduction identifying an index of embodied technical change is important for policy and macro-economic modeling. While it is possible that sector-specific disembodied technical change may lead to the same effect in the data, this mechanism lacks appeal because it is a total black box. In a related point it is perhaps useful to think about the way researchers talk about technical change. When commentators say that the US is more productive now than 10 years ago they typically appeal to the pervasive influence of computers, not "manna from heaven" that falls at a different rate on the high-tech sector. If the high-tech sector is more productive now than it was, or more productive than another sector, it seems sensible that the explanation is that it uses more intensively the capital goods that have experienced rapid technical advance. Finally, on a more formal level, the embodiment approach aligns with the endogenous growth models, such as Aghion and Howitt's (1992) "quality ladders", which emphasize the improvement of quality embodied in intermediate goods as a key source for economic growth.

2.2.3 Bias in price-based measures of q_t

Returning to measurement, there are three sources of bias implicit in the price-based measurement of embodied technical change of equation (3). First, if capital shares differ across sectors, then the sectors' growth rates will differ. We can control for this by constructing capital shares independently of the index q_t. Second, if the price index for consumption already contains some degree of quality adjustment, then our measure of Δq_t will be understated. As seen earlier, BEA uses hedonic-price methods for a number of consumption durables and for housing services, so to minimize the problem we use a price index for consumption nondurables and non-housing services. Third, if disembodied technical change is sector-specific, then our measure of q_t is biased. There is little that can be done about this except to recall that the direction of the bias is ambiguous.[12]

Given our interest in measuring industry-specific rates of embodiment, we develop a simple three-sector input-output model showing that our price-based approach can be extended from aggregate to industry-level data.

2.3 An Input-Output Model

Consider an economy with three sectors, the first sector produces the consumption good c_t and the other two produce two different investment goods i_t and j_t. Each good is produced using a strictly concave, constant returns to scale, production function with capital and labor inputs. For simplicity, we continue to assume that the production functions are Cobb-Douglas. Let us also assume, following the discussion about identification that disembodied technical change z_t is sector-neutral:

$$c_t = z_t k_{ct}^{\alpha} l_{ct}^{1-\alpha},$$

$$i_t = z_t k_{it}^{\beta} l_{it}^{1-\beta},$$

$$j_t = z_t k_{jt}^{\phi} l_{jt}^{1-\phi}.$$

Now, suppose that the three sectors use a different mix of the two capital goods i_t and j_t for production:

$$k_{ct} = (1-\delta) k_{ct} + x_{ct}^{*},$$

$$k_{it} = (1-\delta) k_{it} + x_{it}^{*},$$

$$k_{jt} = (1-\delta) k_{jt} + x_{jt}^{*}.$$

[12]Imperfect competition is a potential source of bias that is outside of our framework. Different mark-ups between industries could lead to changes in the relative prices for reasons unrelated to technology, e.g., changes in regulation or antitrust policy. This is a very interesting line of research that would require a different modeling strategy, so we reserve it for future work.

The two investment goods are assembled into the three intermediate goods $(x_{ct}^*, x_{it}^*, x_{jt}^*)$ in a separate sector using the following technologies:[13]

$$x_{ct}^* = (q_{it}i_t)^{\eta_c}(q_{jt}j_t)^{1-\eta_c},$$

$$x_{it}^* = (q_{it}i_t)^{\eta_i}(q_{jt}j_t)^{1-\eta_i},$$

$$x_{jt}^* = (q_{it}i_t)^{\eta_j}(q_{jt}j_t)^{1-\eta_j}.$$

In the industry data, we observe nominal investment expenditures $(x_{ct}^N, x_{it}^N, x_{jt}^N)$ in the various sectors. Our aim is to recover a quality-adjusted price deflator of investments in each sector (e.g., for x_{ct}^N call this deflator $p_t^{x_c^*}$) such that the relative price $p_t^{x_c^*}/p_t^c$ measures the level of technology embodied in x_{ct}^*. For example, if we take sector c, we would like to measure $\Delta q^{x_c^*} = [\eta_c \Delta q_t^{i^*} + (1-\eta_c)\Delta q_t^{j^*}]$. Following the same steps as in the two-sector model, we have

$$\begin{aligned}
\Delta p_t^c - \Delta p_t^{i^*} &= \Delta q_t^i + (\beta - \alpha)\,\Delta\kappa_{it} \\
\Delta p_t^c - \Delta p_t^{j^*} &= \Delta q_t^j + (\phi - \alpha)\,\Delta\kappa_{jt},
\end{aligned}$$

which implies that

$$\begin{aligned}
\Delta p_t^c - \left[\eta_c \Delta p_t^{i^*} + (1-\eta_c)\,\Delta p_t^{j^*}\right] &= \left[\eta_c \Delta q_t^{i^*} + (1-\eta_c)\,\Delta q_t^{j^*}\right] \\
&\quad + \eta_c\,(\beta-\alpha)\,\Delta\kappa_{it} + (1-\eta_c)\,(\phi-\alpha)\,\Delta\kappa_{jt} \\
&= \Delta q^{x_c^*} + \eta_c\,(\beta-\alpha)\,\Delta\kappa_{it} + (1-\eta_c)\,(\phi-\alpha)\,\Delta\kappa_{jt} \qquad (4)
\end{aligned}$$

Therefore, abstracting momentarily from share differences across sectors ($\alpha = \beta = \phi$), the price index $p_t^{x_c^*}$ satisfies

$$\Delta p_t^{x_c^*} = \eta_c \Delta p_t^{i^*} + (1-\eta_c)\,\Delta p_t^{j^*}.$$

Note that we can use the solution to the problem for the competitive intermediate sector to show that η_c measures the expenditure share i_t^N/x_{ct}^N in the consumption sector and, symmetrically, $1-\eta_c = j_t^N/x_{ct}^N$. Using this

[13]This sector could be one in which certain "managerial" skills are needed to organize production with a variety of inputs, and this sector sells such services. While we don't need to assume that this is a separate sector — assembling the capital goods i and j into the capital input x could be a preliminary stage of production in each sector—it's expositionally convenient to do so.

result, we can calculate the quality-adjusted price index for investment as a Tornquist price index, where changes in the prices of the components of investment are weighted by their respective shares in the industry. Then we can measure industry-specific embodied technical change as the ratio of the Tornquist price index and a similarly defined price index for consumption. As evident from (4), there is still the familiar source of bias stemming from unequal shares across sectors, but as explained earlier, we can account for that bias using shares and capital/labor ratio data at the industry level.

3 Methodology

Our point of departure is Gordon's (1990) seminal contribution to the measurement of constant-quality price indexes for producers' durable equipment. His work is a monumental effort to provide accurate estimates of the quality-bias present in the NIPA official price indexes for numerous investment goods.

3.1 Data Sources

Gordon collected detailed information on prices and goods' characteristics through several sources (from mail-order catalogs to articles in specialized magazines like *Consumer Reports* and *Computerworld*) and applied hedonic techniques as well as more conventional matched-model methods to incorporate quality-adjustment into the official series. The result is a set of quality-adjusted chain-weighted price indexes for 22 different categories of producer's durable equipment goods, covering the period 1947-1983. The goods included in Gordon's calculations were classified into 4 larger groups:

1. **Office Information Processing (OIP):** Office, computers and accounting machinery; Communication equipment; Instruments, photocopy, and related equipment.

2. **Industrial Equipment (IE):** Fabricated metal products; Engines and turbines; Metalworking machinery; Special industry machinery; General industrial (including materials handling) equipment; Electrical transmission, distribution, and industrial apparatus.

3. **Transportation equipment (TE)**: Trucks, buses, and truck trailers; Autos; Aircraft; Ships and boats; Railroad equipment;

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

This taxonomy of goods reflected the official NIPA classification at the time when Gordon was writing. Luckily, the current NIPA classification has remained remarkably similar, except for the first group of goods. The BEA now distinguishes explicitly among computers and peripherals, and other office and accounting machinery. Moreover, since 1999 software is recorded as investment.[14] This first group of goods is now called information processing equipment and software (IPES) and the entire set of 24 equipment investment goods is called nonresidential private fixed investment in equipment and software.

The evolution of the expenditure shares for the four groups above is remarkable. Figure 1 reports data on the shares from 1947-2000, computed from Table 5.8, in the *Survey of Current Business* (SCB). As expected, investment in IPES grew at a much faster rate than any other type of equipment investment in the past 50 years and now accounts for almost half of total investment expenditures. What is particularly striking is the importance of the recently added software investment which in the past two decades has grown even faster than computer investment. In 2000, software expenditures represented nearly 20 percent of the total investment in equipment, almost as much as the entire expenditures of the US economy on transportation equipment.

3.2 Our Methodology

We use some simple forecasting techniques to extrapolate, for the period 1984-2000, the quality-bias implicit in some of the official price series, using as a benchmark Gordon's computations, which covered the period 1947-1983. In addition to providing a longer sample period for statistical analysis, developing quality-adjusted prices for the 1980s and 1990s gives us the opportunity to address whether embodied technical change has accelerated in the past two

[14] Previously, only software embedded in equipment by the producer of that good was counted as investment. That type of software (e.g., Microsoft's Windows operating system already installed on new PC's) is still counted as part of the value of investments in other equipment goods.

decades. If it has, then it may help explaining the productivity surge of the late 1990s.

To construct the extended quality-adjusted price series, we update and improve upon the analysis in Krusell et al. (2000). The key idea is to exploit the fact that we have a long time series (1947-1983) of both Gordon's quality-adjusted and official NIPA price indexes. Using these pairs of price indexes, we estimate for different types of assets an econometric model of Gordon's quality-adjusted price index as a function of a trend and a cyclical indicator, augmented with the current and lagged values of the official price series. Using the coefficient estimates and the fact that all the regressors are available until 2000, we extrapolate a quality-adjusted series from 1984 to 2000.

The admittedly disputable assumption for the accuracy of our approach is that the data generating process for the quality-bias in the official price indexes has not changed since 1984. For this reason, we do not implement this procedure for most of the goods included in the IPES category. In particular, we do not use it for computers and peripherals, since BEA provides a reliable constant-quality price index for that category. We also cannot apply it for software, as data on software investments were not available at the time of Gordon's analysis. Instead, for software we use the official price indexes. By proceeding in this way we are trying to minimize the bias that arises if the key assumption underlying our estimation and forecasting methodology is violated.

It is somewhat comforting that extrapolation is also used by other authors and by the BEA itself, when better sources of data are not available. For example, the official NIPA price index of pre-packaged software (which is quality-adjusted) is extended prior to 1985 using an indicator time series equal to 60 percent of the annual change in the NIPA price index for computers and peripherals, where this percentage corresponds to the average difference for 1985-1997 between the annual rate of change in the computer price index and the pre-packaged software price index. Moreover, some authors, e.g., Jorgenson and Stiroh (2000a), have drawn from the existing empirical results of microstudies on switching gear equipment and spreadsheets to construct constant-quality indexes in order to deflate software and communications investments.

Finally, we have to face the fact that the introduction of current and lagged values of official price variables in our regression implies a trade-off between accuracy in forecasting and a potential "endogeneity" problem that arises insofar as shocks to quality not controlled for in the regression affect the *unadjusted* price level. To avoid this endogeneity problem, we could have omitted current and lagged official price variables from the regression and we could have forecasted Gordon's quality bias $q_t^{i_j^*} \equiv p_t^{i_j^*}/p_t^{i_j}$ only through a constant and a trend. When we tried this strategy, our results were not significantly different for most assets.

3.3 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 chain-weighted price index constructed by Gordon (1990, Appendix B) for the period 1947-1983. Then we collect the official NIPA chain-weighted price indexes of the investment goods above for the period 1947-2000, taken from Table 7.8, SCB. For each category of good j, we select data on the first part of the sample (1947-1983) and we estimate an econometric relationship between the Gordon's series and the official NIPA series, augmented with a linear trend, lags of a business-cycle indicator, and lags of the official price index.[15]:

$$p_t^{i_j^*} = c + \beta_1 t + \beta_2 p_t^{i_j} + \beta_3 p_{t-1}^{i_j} + \beta_4 \Delta y_t + \varepsilon_t^j, \tag{5}$$

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 official price index, Δy_t is the growth rate of 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 good from the original sample.

3.4 Model specification

A number of standard econometric issues arise in the choice of the model specification. The crucial issue is the order of integration of the series. In approaching this problem, first, we have tested for the presence of a unit root in each price series (both quality-adjusted and official), using various

[15]The growth rate of real GDP was used as the cyclical indicator. We followed a mixture of Akaike and Schwartz criteria to select the optimal order lag in each equation.

versions of the Augmented Dickey Fuller and the Phillips-Perron tests. We cannot soundly reject the null hypothesis of a unit root for any of the series.[16] Next, we tested for cointegration between the quality-adjusted and official price series using the Johansen test. Once again, in the vast majority of cases we could not reject the null of cointegration. In a few cases we could reject it at a confidence level of 10 percent, but not at 5 percent. From this battery of tests we inferred that, in general, the quality-adjusted and the official price series are $I(1)$ and cointegrated. This suggests that estimating the econometric relationship in levels exploits the long-run comovements of the series and generates a more reliable forecast than using first-differences.[17]

We use a time trend, lags of the official price index and lags of GDP growth in the specification. Notice that we exclude lags of the dependent variable. An alternative specification with lags of the dependent variable would have necessitated multi-step forecasting methods where 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.

Table 1 contains the results of the 20 equations estimated for each category of goods among industrial, transportation and other equipment, and figures 2-7 plot the official and quality-adjusted series, including the forecast with the corresponding standard errors. The coefficient on the linear time trend in table 1 determines the extent of the quality-bias in the official price-index. For assets such as agricultural machinery (e.g., harvesting machinery, poultry equipment, plows, fertilizing machines), electric equipment (e.g., heating equipment, lighting fixtures, medical X-ray units), metalworking machinery (e.g., power driven hand tools, welding tools, cutting tools) and tractors the estimate of the trend was small and insignificant, indicating that quality-bias in the official price is unimportant. However, the coefficient indicates large declines in other categories: 15 percent for aircraft, 6.1 percent for engines and turbines, 4.6 percent for service industry machinery (e.g., food products machinery, water heaters) and for special industry ma-

[16] Structural breaks could be present in some of the series (e.g., aircraft). It is well known that the existence of breaks biases the test against rejecting the null hypothesis. In the most obvious cases, we split the sample in two and tested for unit root in each subsample, without major changes in the results.

[17] We did plenty of sensitivity analysis on those price series for which the evidence on cointegration was weaker. Notably, we used different specifications of the model in first differences, with very little change in the final result.

chinery (e.g., textile woodwork, and printing machinery). Besides the trend component, the figures show that the current value and the lags of the official price index together with the cyclical indicator capture medium to high frequency movements in the price series reasonably well.

3.5 Quality-Adjusted Price Indexes for IPES

Information processing equipment and software is the group of investments whose share has increased fastest and whose price has fallen most sharply. This is particularly evident for computers and software.

To construct a quality-adjusted price index for computers and peripherals, we combine two data sources. First, Gordon provides a quality-adjusted chain-weighted index (Table 6.12, column 2) for computers and peripherals for 1947-1983. Second, BEA calculates quality-adjusted price indexes for computers and peripherals starting from 1958 (Table 7.8, SCB). Thus, we use Gordon's index for the period 1947-1957 and use the quality-adjusted BEA series for 1958 onward.[18] Figure 8 which plots the log of the price index for computers and peripherals shows its dramatic fall over the last 50 years, at an average rate of nearly 19 percent per year.

We exploit the 1999 comprehensive revision of the NIPA that provides price series for various types of software investment starting from 1959. The methodology used to construct this price is described in detail in Parker and Grimm (1998). Three different prices series (with the corresponding shares) are supplied 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 price-index for prepackaged software is computed us-

[18]Krusell et al. (2000) exploit the large empirical literature on the derivation of quality-adjusted price indexes for PCs, mainframes and peripherals based on hedonic-methods and extend the Gordon series until 1992. We also constructed a second series for computers and peripherals using Gordon's price series until 1983. For 1984-1992, we use the series in Krusell et al. and for 1993 onwards, we use the BEA price series (they are both chain-weighted). The resulting price index and our benchmark index are similar in the first half of the sample: the average decline rate of the quality-adjusted price is around 16 percent from 1947 to 1973 for both series. However, in the second part of the sample, the benchmark series declines at an average rate of 16.5 percent versus an average 20 percent of the Gordon-Krusell et al. series. The discrepancy is concentrated in the period between the late 1980s and the early 1990s. Overall, it seems that our benchmark series provides a conservative estimate of quality improvements in computers.

ing both matched models 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. The price of pre-packaged software has been falling at the fastest rate (10.7 percent per year on average), as evident from Figure 8. 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 in the subsequent years (1979-2000).[19]

There are a few studies that can be used to check the adjustment BEA makes for prepackaged software. Brynjolfsson and Kemerer (1996) provide a detailed study of the price of commercial spreadsheet applications from 1987 to 1992. They report a fall in the quality-adjusted price of around 16 percent per year, notwithstanding the small rise in nominal prices, a slightly higher number than the 15 percent estimated by Gandal (1994) for 1986-1991. The average rate of change of the BEA price index for prepackaged software is 13.2 percent per year in the same period, suggesting that the quality-adjustment in the official data may be fairly accurate.[20] Nevertheless, the fact remains that prices for the other two types may be overstated substantially. In absence of better measurement, we take a conservative approach and use the official price index.

Communication equipment and instruments are other categories of goods for which we would expect a sharp fall in price. Unfortunately, we are not aware of any systematic study of the quality-bias in their price index: BEA has constructed a constant-quality index only for digital switching equipment (part of communications), whose technology is similar to that of computers (Grimm, 1997). However, within telecommunications equipment especially there are goods whose quality has improved vastly (e.g., fiber-optic cables). Therefore, we use the same forecasting procedure we applied to the goods other than information processing equipment: we start from the quality-

[19] We have obtained the aggregate price series for software investments from the three price series above and their respective shares, through a Tornquist aggregation procedure (see the next section for details).

[20] The fact that the BEA number is slightly lower can be attributed also to the fact that prepackaged software does not only include spreadsheets. Oliner and Sichel (1994) estimate to a 3 percent the price decline for a bundle of prepackaged software programs including spreadsheets, word processors and databases. So it is possible that the price decline for software other than spreadsheets has been slower.

adjusted series calculated by Gordon until 1983 and we estimate an econometric model in order to predict the quality-bias over the official price series for the post 1983 sample. The relevant econometric specifications for these equations are also reported in the Appendix: the coefficient on the time trend confirms our intuition, as it stands at -6.65 percent for communication equipment and -4.6 percent for instruments (e.g., pumps and compressors, measurement instruments, photocopying equipment). Figure 2 shows the dramatic difference between the official price index and our estimated quality-adjusted price index for communications. In particular, since the mid-1970s, our estimated constant-quality price index falls at a rate of 6.6 percent per year vis-a-vis the official price index, which is essentially unchanged.

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 official NIPA series (Table 7.8, SCB). It is clear that this conservative choice should not have large effects, since this type of investment has never accounted for more than 3 percent of total equipment investment in the past 30 years and its share has been falling monotonically over time, a sign that its relative price has not fallen by much.

4 Aggregate Results

4.1 Tornquist aggregation

In order to aggregate the price indexes of each category into a unique price index for equipment and software, we use the Tornquist procedure (a chain-weighted method) used, for example, by Gordon (1990). The first step is to compute the nominal investment expenditure shares of each good for the whole period 1947-2000. The shares are constructed from Table 5.8, SCB as the ratio between the current dollar value of investment in that good and the current dollar value of total private nonresidential equipment and software investments. Let $s_t^{i_j}$ be the nominal share for investment good $j \in \{1, 2, ..., N\}$ at time t, and let $p_t^{i_j^*}$ be the corresponding quality-adjusted price index for investments of type j. Denote the aggregate quality-adjusted price index of equipment investment at time t as $p_t^{i_e^*}$. The change in the aggregate price index is defined as

$$\Delta p_t^{i_e^*} = \sum_{j=1}^{N} \ln \left(\frac{p_t^{i_j^*}}{p_{t-1}^{i_j^*}} \right) \left(\frac{s_t^{i_j} + s_{t-1}^{i_j}}{2} \right), \tag{6}$$

and the final aggregate price index is simply

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

4.2 Quality-bias in the official NIPA price index

This aggregate quality-adjusted index allows us to analyze the "drift" of the equipment price series, i.e., the quality-bias in the official price index for equipment. If we denote the official NIPA price index for nonresidential equipment and software investment (obtained from Table 7.8, SCB) as $p_t^{i_e}$, we can measure the drift from the ratio $\frac{p_t^{i_e^*}}{p_t^{i_e}}$. Figure 9 reports our measure of the quality-bias. Recall that this bias stems from the fact that for a number of goods we use different price indexes than BEA, with stronger quality-adjustment. On average, we find the annual quality-bias is about -2.5 percent, and as expected it is slightly lower in the last part of the sample, where goods such computers and software (for which we use the official NIPA deflator) start to weigh substantially in the aggregate. Our measure of quality-bias levels off at around 2.5 percent since the mid-1980s and, by construction, it shows very little fluctuation.

4.3 Base consumption price index

To calculate an aggregate index of embodied technical change we follow the one sector model outlined in Section 2. Thus we need to choose a benchmark price index for goods other than equipment produced domestically. To properly measure the pace of quality improvement in equipment we need an "unadjusted" price of consumption. In order to verify the sensitivity of our final results to this choice, we calculate this price index in several ways. Our preferred version is a price index for consumption nondurable goods (excluding energy expenditures) and non-housing services obtained from the official chain-weighted price indexes (Table 7.5, SCB) weighted through a Tornquist aggregation by the respective expenditure shares (obtained from Table 2.2, SCB). We also use the same methodology to construct a price index that includes energy expenditures and housing services, and one that also includes nonresidential structures. These three price indexes are remarkably similar, as they all grow at an annual rate of nearly 3.8 percent. We opt for the first index for two reasons: first, energy expenditures can be exogenously affected by fluctuations in the oil price that have little to do with technology, and, second, as mentioned earlier, expenditures on housing services are quality-adjusted.

4.4 An aggregate index of equipment-embodied technical change (1947-2000)

If we now denote the consumption price index as p_t^c, our aggregate index of equipment-embodied technical change is

$$q_t^e = \left(\frac{p_t^{i_e^*}}{p_t^c}\right)^{-1}. \tag{7}$$

In Figure 10, we plot the growth rate in our measure of q_t^e over the sample. Two important facts emerge: first, the index implies a very large growth of embodied technical change in the past half-century, on average 4 percent per year; second, since in the mid-1970s the pace of embodied technological improvement has accelerated: the index grows at a rate of roughly 3.2 percent until 1975, and at a rate of 4.9 percent after 1975.[21] In the 1990s the growth has been spectacularly high, reaching an average annual rate of 6.35 percent.

Table 3 reports the pace of quality improvement in each of the 24 asset categories defined in section 2. Not surprisingly, the largest gains in productivity are embodied in high-tech goods: the level of productivity embodied in computers grew on average at 23.5 percent per year, with a peak at 26 percent between 1960 and 1980. Quality improvements in prepackaged software also advanced at a swift pace, averaging 15.3 percent over the period, with a peak of 18.1 percent in the 1970s. Interestingly, for both computers and software there seems to have been a slight deceleration in the 1980s and 1990s compared to the previous two decades. The productivity level of communication equipment advanced at the rate of 8.7 percent per year

[21]In computing these growth rates, we have excluded the 1975 outlier from *both* subsamples.

over the period 1947-2000. In contrast to computers and software, the 1990s witnessed a sharp acceleration in the rate of embodied productivity growth for communications, reaching 12.9 percent Another asset category that according to our estimates has embodied enormous productivity improvements is aircraft: its quality has increased 8 percent per year on average, and 11 percent in the last decade. At the same time, we find categories with very little quality improvement, such as agricultural machinery, railroad equipment, and perhaps surprisingly own-account software.[22]

4.5 Equipment investment and capital stock in efficiency units

The price series $p_t^{i_e^*}$ can be used to deflate the nominal investment series in order to obtain a measure of the amount of resources effectively invested in equipment and software in the US economy in the past 50 years. By dividing the NIPA series of nominal private investment in nonresidential equipment and software in current dollars (Table 5.8, SCB) by the quality-adjusted chain-weighted price series $p_t^{i_e^*}$, we obtain real investment expenditures in efficiency units, i_{et}^*. In Figure 11, we plot the growth rate of this series together with the growth rate of official real investments, i_{et}. The latter series is constructed dividing the nominal investments by the official price index $p_t^{i_e}$. The quality-adjusted series grows at an annual rate of 8.9 percent, around 2.55 percent in excess of the official series, in line with our results on the quality bias above. The pace of investment in the last decade is striking, as the growth rate reached on average 13 percent per year.

With the series for investment in efficiency units in hand, we can recover the evolution of the aggregate productive capital stock of equipment in efficiency units k_e, using the perpetual inventory method and a constant geometric rate of depreciation:

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

where δ_t^e is the time-varying *physical* depreciation rate for equipment. The BEA reports detailed economic depreciation rates (d_t^e) by asset category (BEA, 1999, Tables A-B-C). Depreciation rates for software are provided by Parker and Grimm (2000) as follows: 55 percent for pre-packaged software

[22] As explained earlier, for own-account software we use the official price index which is not quality-adjusted by BEA.

and 33 percent for own-account and custom software. Fraumeni (1997) describes the methodology to calculate these depreciation rates: in most cases, the BEA still uses the numbers provided by Hulten and Wykoff (1981), which include both physical decay and obsolescence. In fact, *economic* depreciation for an asset of type j is defined and measured by the BEA as the change in the value of an asset associated with the ageing process, so as such it is composed by a pure age effect (physical decay δ_t^j due to tear and wear) and a time effect (obsolescence, due to the change in the relative price of capital in the period, i.e. q_t^j/q_{t-1}^j). Thus,

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

Therefore, we need to separate the physical decay component δ_t^j from the BEA measures of d_t to appropriately construct the aggregate series for k_{et}. Gort and Wall (1998) point out that using (8) with the quality-adjusted investment flows and the BEA depreciation rates –as for example in Hulten (1992)– solves only half of the problem.

For each asset category j, we use the official depreciation rates and equation (9) –where we measure q_t^j through the relative price of asset j– to back out the actual physical decay rate δ_t^j. We then aggregate these physical depreciation rates in every year using the nominal shares of each asset in the total equipment capital stock for that period s^{k_j} (we compute these the nominal shares from the BEA Fixed Assets Tables), as suggested for example by Whelan (2000), i.e.

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

The aggregation yields a series for δ_t^e.[23] Figure 12 plots three series: the official depreciation rate d_t^e, our computed series δ_t^e, and a smoothed series obtained by fitting a quadratic polynomial. 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

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

variability implicit in the price indexes looks stationary as demonstrated by our fitted series which moves very little around 10 percent. The key finding is that basically the entire rise in economic depreciation can be attributed to losses in the value of assets because of obsolescence. The rise in the importance of the obsolescence component over time is due to the increasing share of high-tech goods in the economy. The volatility of the implied series is related to the high variance of relative price changes over the period. To parallel the practice of the BEA of using relatively constant depreciation rates, even for long periods, in what follows we always use our smoothed series. Our calculations of the quality-adjusted productive capital stock based on quality-adjusted investment flows and purely physical decay rate suggest that equipment stock grew at an average rate of 8.8 percent per year from 1947.

We also computed an alternative capital stock based on BEA economic depreciation and the BEA price index for investments (the "pseudo-official) through the same geometric depreciation rule. Our analysis suggests that the growth of this series is on average 3 percent lower than the quality-adjusted series: in particular, $10 percent$ of the underestimate in the pseudo-official series is due to the misleading presence of obsolescence in the official depreciation rates, and the residual $90 percent$ is related to the missing quality-adjustment in the price-indexes.[24]

4.6 IPES Investments and Capital

Aggregate efficiency units of investments in IPES i^{*}_{ipes} grew at a striking 16.5 percent per year on average in the postwar period, while the official NIPA series grows at an annual rate of 12.8 percent, implying that the average quality-bias for IPES goods not accounted for by BEA (due essentially to communications and instruments, since for all other categories we adopted the BEA price indexes) could be around 3.7 percent per year. Our compu-

[24]We also compute the difference between our series and a series where investments are valued in consumption units and economic depreciation is used instead of physical decay. The overall difference between the annual growth rate of our series and this series is 3.7 percent. Gort and Wall (1998) show that if both the physical decay rate δ and the rate of obsolescence Δq (embodied technical change) are constant, then the difference between the two series should be exactly Δq, which is 4 percent for our series. Thus, given the stationarity of δ^{e}_{t}, the 0.3 percent differential should be attributed to the large variations of Δq_t over the time period considered.

tations suggest that in the period 1991-2000 the growth rate of investments in IPES reached 19.3 percent per year.

In order to compute a rate of physical decay for the stock of IPES goods, we repeat the same procedure outlined above and plot the results in Figure 13: our estimated depreciation rate is substantially lower than the official series (the difference is between 5 percent at the beginning of the sample and 7 percent at the end of the sample); moreover, our implied rate of physical decay shows some rise at the beginning of the 1980s, consistently with the BEA observation that the physical depreciation rate for computers increased from 27 percent to 31 percent after 1978. It is interesting to note that although computers and software have very high depreciation rates, the overall depreciation rate (even before accounting for obsolescence) for IPES is quite low because computers and software represent a very low share of the capital stock: until 1990 they made up for less than 28 percent of the total stock of IPES goods.

The resulting IPES productive capital stock grows on average at 16.3 percent per year, vis-a-vis an annual growth rate of the pseudo-official series of roughly 12.3 percent (see Table 2). For IPES goods, our calculations suggest again that roughly 10 percent of this underestimate of capital growth is due to the misleading presence of obsolescence in the official depreciation rates. The residual 90 percent is due to our estimated drift in the price index.

4.7 Hulten's index of the technological gap

Hulten (1992) is the first paper to have used Gordon's quality adjusted prices series to measure embodied technical change. Another key contribution of Hulten's paper is to point out that one can use the estimates of embodiment to measure the "embodied technological gap" between the average machine in the economy and the leading edge machine. Let Q_t^e be the average efficiency level embodied in equipment and software, i.e.

$$Q_t^e = q_t^e \frac{i_{et}}{\widetilde{k}_{et}} + (1 - \delta_{t-1}^e) q_{t-1}^e \frac{i_{e,t-1}}{\widetilde{k}_{et}} + ...$$

where i_{et} and $\widetilde{k}_{et}$ denote the "unadjusted" investment and capital stocks (i.e., in consumption units). Then it is immediate that $Q_t^e = k_{et}/\widetilde{k}_{et}$. Hulten proposes the following index to measure the wedge between the best practice level of technology, q_t^e, and the average level in that year Q_t^e:

$$\Gamma_t^e = \frac{q_t^e - Q_t^e}{Q_t^e},$$

where we use the letter "Γ" to denote the fact that this measure captures the "technological *gap*".[25] Rapid investment growth leads to a reduction of this index, while in times of stagnant investment the technological frontier gains distance compared to the average practice in the economy.

Figure 14 plots the evolution of this index for aggregate equipment and for IPES goods. The index for equipment stands at about 10 percent in the 1950s, then rises to 20 percent in the 1960s and after a decade in which it remains stationary, it keeps rising in the 1980s-1990s to reach roughly 40 percent. This represents a remarkable upsurge in the average technological gap of the economy.[26] Interestingly, although the gap for IPES remains constantly higher than the gap for total equipment over the whole sample period, the wedge between the two opens up dramatically in the period from the mid-1970s to the mid-1980s, while it closes down in the 1990s, when the gap for IT equipment and software remains fairly constant. This pattern could be explained by the substitution taking place in the economy across different types of equipment goods, following the sharp changes in the relative prices. The period 1975-1985 witnessed phenomenal technological advances in the high-tech industries, but those technologies were not widespread in the workplace yet. Later, as investments in new technologies start growing fast and start substituting expenditures on other goods, the gap for IPES closes down gradually.

[25] Hulten calls this measure the "elasticity of embodiment" because it can be shown that it also measures how an increase in unadjusted capital feeds back into the growth rate of the average level of efficiency (see Hulten, 1992, page 970).

[26] Hulten (1992) originally computed estimates the elasticity of embodiment only for the manufacturing sector. He reports an average value of 23 percent for the period 1949-1983, and 22 percent for the sub-period 1974-1983. For the same sample periods, our estimates are respectively 17 percent and 20 percent, hence fairly in line with his original findings. The differences can be attributed to a number of factors (updated estimates for computer and software investments, sectoral differences, and different rates of depreciation used to construct the capital stock, among others).

4.7.1 A Remark on Embodied Technical Change and Wage Inequality

Hulten's index can be used to understand the role of education for economic growth. In their influential paper, Nelson and Phelps (1966) argue that educated labor helps implementing new technologies, so the distance between the "theoretical frontier" (q_t^e) and the actual practice (Q_t^e) depends on the endowment of skills in the economy. It also follows that the demand for skills and the equilibrium skill premium are proportional to the speed at which technology advances compared to average practice. The behavior of this index squares with the well-known facts on wage inequality. Hulten's index for aggregate equipment is rises steadily, except for the 1970s, which is the only decade in the past 40 years over which the educational premium has been falling. In Figure 15 we reproduce a series of the returns to college education from Goldin and Katz (2000) together with a smoothed version of the series for the Hulten index plotted in Figure 14. Goldin and Katz report the returns to college computed through the decennial Census from 1940, so to obtain a continuous time series, we interpolate linearly between successive decades. The two series move remarkably in tune at low frequencies, corroborating the view that the Hulten's index may have an important role in the theory of skill premia.

4.8 Capital structures

At this point of the analysis, we need to integrate investment in structures into our framework. To deflate nominal investments in structures, we use the official price indexes. The price index for structures in the postwar period grew slightly faster (0.4 percent) than the price index for consumption, suggesting no quality improvement. However, according to Gort, Greenwood and Rupert (1999) this is an understatement: they estimate that structure-specific technical change advanced at a rate of 1 percent per year in the postwar period. In this sense, by using the official figures we might underestimate the growth in capital structures. Aggregating capital equipment and structures together requires three steps: first, constructing a deflator for aggregate investments weighting the two deflators for equipment and structures by their nominal investment shares; second, constructing an aggregate depreciation rate. In doing so we use the official depreciation rate for structures, which we measure to be roughly 2.8 percent [27]; third, we construct the aggregate capital stock using the perpetual inventory method and a constant geometric rate of depreciation.

A by product of our calculations is an index of embodied technical change for aggregate capital. Our series grows, on average at a rate of 2.6 percent per year. Hobijn (2000) proposes an alternative approach to the estimation of capital embodied technical change, based on the calibration of a structural vintage model. In his paper, he estimates an average annual growth rate of embodied technical change of roughly 2.5 percent for the US economy. Not only are these two estimates are very close, but the time pattern of the two series is remarkably similar, which is very encouraging, in light of the different methodologies used.

4.9 "Statistical" growth accounting

A natural question to explore in our framework is how much of the postwar output growth performance can be attributed to embodied technical change and, more specifically, to quality improvements in IPES.

We start from the accounting framework of our one-sector model, where the aggregate production function takes a Cobb-Douglas specification and output is unadjusted. We focus on the domestic private business sector of the US economy. Standard computation of the labor share in this sector leads an average value for $1-\alpha$ of .64 for the period 1947-2000.[28] We measure directly real output growth in the private business sector from the NIPA (Table 1.8, SCB). To measure labor input l_t, we use the Ho and Jorgenson (1999, Table 5) index which is carefully quality-adjusted accounting for changes in the composition of the labor force by age, gender, education, and employment class, thus it is possible to distinguish between "raw labor" n_t and quality of labor h_t, where $l_t = h_t n_t$.[29] To identify the contribution of growth in IPES

[27] We compute this number by aggregating asset-specific BEA depreciation rates with their nominal capital stock shares. Gort, Greenwood and Rupert (1999) separate the obsolescence component from the economic depreciation rate and arrive at an estimate of the rate of physical decay for structures of 1.9 percent . This is consistent with our number, given their estimate of 1 percent per year of unmeasured technical change embodied in structures.

[28] Although the estimated share presents some small variation over the sample (from .59 in 1950 to .67 in 1980, down to .64 in the 1990s), we set it to the average value for consistency with our theoretical framework.

[29] The Ho and Jorgenson index is constructed for total private sector, including business

goods for the growth of the aggregate capital stock between time t and t', we use the Tornquist decomposition

$$\Delta k_{t-t'} = \frac{\left(s_t^{k_{other}} + s_{t'}^{k_{other}}\right)}{2} \Delta k_{other,t-t'} + \frac{\left(s_t^{k_{ipes}} + s_{t'}^{k_{ipes}}\right)}{2} \Delta k_{ipes,t-t'} \qquad (10)$$

where $s_t^{k_{ipes}}$ denotes the nominal share of IPES goods in the total capital stock at time t, $s_t^{k_{other}}$ is the nominal share of all other capital goods, and $\Delta k_{t-t'}$ is the growth rate of the total capital stock (equipment plus structures) between time t and time t'. The results of our growth accounting exercise are shown in Table 4 for the period 1948-1999.[30]

The contribution of capital to output growth is estimated to be nearly 54 percent, that of labor input 32 percent, and the contribution of residual TFP growth just above 14 percent. The contributions of both capital and labor grow steadily over the sample, at the cost of TFP, whose contribution ends up being negative during the past 20 years. Within capital, we distinguish between "quantity", i.e. capital stock in consumption units $\tilde{k}_t$ and quality Q_t (computed as above). Out of the 54 percent average contribution of capital, 21 percent is due to quality improvements in total capital: in the 1990s this number reaches 31 percent. Interestingly, the contribution of quality improvements in IT capital (i.e., IPES goods) grows enormously over the sample, from just 1.4 percent in the 1950s to 12.5 percent in the 1990s, averaging 6 percent in the postwar period. Within labor input instead the contribution of quality embodied in workers was very high in the 1950s, but it falls sharply in the 1970s and the 1980s, possibly due to the entry into the labor force of the baby-boom generation.

Our two-sector model of section 2 is consistent with both an accounting framework where output is unadjusted (à la Solow) and one where output is adjusted for quality (à la Jorgenson). The latter option is preferred by a number of authors (e.g., Hulten, 1992, Jorgenson and Stiroh, 2000a, 2000b), thus for comparability, we also provide a growth accounting exercise where we adjust output for quality. To compute constant-quality output, we compute

sector, private households and non-profit institutions. Private households are not a major source of employment, but it remains a slight discrepancy between our output measure and the labor index due to the non-profit sector.

[30] The period starts a year later and ends a year earlier than our standard sample (1947-2000) because the labor index constructed by Jorgenson and Ho is available spans 1948 to 1999.

a Tornquist-type price deflator for personal consumption expenditures (from Table 101, SCB) and nonresidential private fixed investments, where we use our quality-adjusted price index for the second component. Output growth computed in this way is on average 0.3 percent higher, but this adjustment is twice as big in the 1990s, implying a smaller contribution for capital and labor and a larger contribution for disembodied productivity which is not negative any longer, but it remains positive and increases from the 1980s to the 1990s.

We computed the bias in the two-sector model using the industry data (discussed below). Our calculations imply that from 1977 to 1999 the bias would increase the rate of embodied technical change by about 1 percent per year. This is due to the growth in the real capital-labor ratio and the larger capital share in nondurable goods manufacturing.

How do our results compare with those in the literature? Hulten (1992) found that embodied technical change explained 20 percent of residual output growth, i.e. output growth net of the contribution of all other inputs for 1949-1983 in the manufacturing sector. Our estimate for the whole economy is much higher, nearly 40 percent in the same period for the case where output is adjusted. Jorgenson and Stiroh (2000a, Table 2) adjust output for quality and report the contributions of various inputs for the period 1959-1998: in their calculations the quantity of capital contributes for 36 percent, capital-embodied quality improvements for 13 percent and labor input for 34 percent which implies a contribution for disembodied productivity of 17 percent. Thus, although we find a similar contribution for capital in efficiency units, our estimates suggest that a much larger fraction is due to quality (19.6 percent) and a smaller fraction to quantity growth. We also compute the contribution of labor to be roughly 3 percent smaller, which boosts up by the same amount our estimate of the share of TFP growth.

4.10 "Equilibrium" growth accounting

One disadvantage of "statistical" growth accounting is that it does not isolate the reasons for factor accumulation. As a result, such growth accounting is silent about whether, for example, the quantity of capital increased because of disembodied or because of embodied technical change. By contrast, a structural equilibrium model, like the one sketched in section 2, 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 embodied in capital q_t, quality improvement embodied in labor h_t, and disembodied productivity z_t. We assume that all three sources of growth are exogenous.

Let us now augment the one-sector model in Section 2 with the household side, under the assumption of risk neutrality and deterministic environment. Substituting marginal productivities of the factors for the equilibrium prices, as established by equation (2), into the Euler equation for the households leads to the equilibrium relationship

$$\frac{1}{q_t} = \beta \left[\frac{(1-\delta)}{q_{t+1}} + z_{t+1} \alpha k_{t+1}^{\alpha-1} l_{t+1}^{1-\alpha} \right].$$

Taking logs of the equation above and constructing the difference $\Delta k_t = \ln(k_{t+1}) - \ln(k_t)$, one obtains

$$\Delta k_t = \frac{1}{1-\alpha}\Delta q_t + \frac{1}{1-\alpha}\Delta z_t + \Delta l_t - (\Delta q_t - \Delta q_{t-1}), \tag{11}$$

where the last term captures the fact that the higher is the expected obsolescence, the lower is the growth rate of capital Δk_t between t and $t+1$. Using (11) into the relation

$$\Delta y_t = \Delta z_t + \alpha \Delta k_t + (1-\alpha)\Delta l_t$$

obtained from the aggregate production function, one arrives at the following decomposition of labor productivity growth:

$$(\Delta y_t - \Delta n_t) = \frac{1}{1-\alpha}\Delta z_t + \left[\frac{\alpha}{1-\alpha}\Delta q_t - \alpha(\Delta q_t - \Delta q_{t-1}) \right] + \Delta h_t$$

In Figure 16, we plot the three sources of growth of the US economy: it is clearly visible how embodied technical change dwarfs both other components, especially in the past 30 years. Given our estimate of α and the estimated average growth rates of q_t and h_t, respectively 2.6 percent and 0.6 percent, we conclude that 59 percent of growth in output per capita from 1948-1999 is explained by quality improvements embodied in 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 16 percent is due to disembodied productivity growth. Our results are in line with the equilibrium growth accounting exercise of Greenwood, Hercowitz and Krusell (1997) who quantified the contribution of q_t for the whole economy to be 58 percent.[31]

4.11 The Recent Productivity Surge: Cycle or Trend?

It is undeniable that the performance of the US economy in the second half of the 1990s has been absolutely remarkable. According to our calculations, quality-adjusted GDP growth in the private sector averaged 5.2 percent per year from 1995 to 1999, while the average in the preceding two decades had been just below 3.5 percent. This striking acceleration in output growth has generated a vibrant debate among economists on what its origins are. To begin with, it is of interest understanding whether investments in IT are behind these record productivity levels; second one would like to distinguish cyclical from structural forces to predict the persistence of such productivity revival; finally, it seems important to measure how extended across industries these productivity gains are.

There are two alternative views on this. The "optimistic" view (Jorgenson and Stiroh 2000, Oliner and Sichel 2000) is that IT investments are key to the productivity acceleration of the late 1990s, they are a structural force and gains are widespread across industries. For example, Oliner and Sichel compute that over 40 percent of the labor productivity acceleration of the late 1990s compared to the 1973-1995 period is due to capital deepening in IT-related goods. Jorgenson and Stiroh's computations imply a slightly small figure, around 35 percent. In both calculations, TFP accounts for the remaining part, with labor quality playing a very small role.[32] They both document that the TFP acceleration is large even in *non* IT-related industries. These authors do not distinguish between cyclical and structural component in their decomposition. A more skeptical position on the role of IT investments is maintained by Gordon (2000): 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 in IT related sectors, with other industries gaining extremely little from the

[31] One could further refine this decomposition, by endogenizing human capital accumulation h_t. Then, the growth in h_t would be partially explained by q_t and partially by z_t, so we would restrict to our driving forces of growth to only two components.

[32] Both studies, however, report that capital deepening in *non*-IT goods has decelerated and therefore has contributed negatively.

"IT revolution".[33]

In Table 5 we report a decomposition of the acceleration in labor productivity of the late 1990s into capital deepening, labor quality effects and TFP, as implied by our data. We measure an acceleration in labor productivity from 1973-1995 to 1995-1999 of roughly 0.87 percent per year, so somewhat smaller that the number reported by Gordon (2000) and Oliner and Sichel (2000), but closer to Jorgenson and Stiroh (2000a) and the BLS. The first column confirms that capital deepening is a driving force of the recent acceleration, contributing over 42 percent. This number hides a difference with the previous studies: in our calculations, IT goods (i.e., IPES categories) account for 25 percent of the total productivity surge, with other goods also giving a positive contribution of around 17 percent. It is worth noting that the entire surge of capital deepening is due to quality improvements, with the quantity of capital (in consumption units) contributing negatively. However, the dominant force, as found in the existing studies is TFP whose acceleration, after the dismal performance of the 1980s, compensates for the slowdown in labor quality.

To analyze the issue of cycle vs. trend, we have split each component of labor productivity into trend and cycle using a Hodrick-Prescott filter. The standard 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, i.e. with a lower λ one should expect to obtain a lower bound for the cyclical component. We find that the cyclical component in the recent productivity acceleration is bounded between 30 percent and 90 percent, hence Gordon's estimate of one third could well be conservative.[34] From Table 5, we also conclude that the deceleration in labor productivity is mostly a cyclical phenomenon (probably associated to a strong labor market including in the work-force the bottom tail of the skill 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 allow to disentangle clearly whether the surge in TFP belongs to the cycle or to the

[33]The comparison among these three papers is based on Table 5 in Stiroh (2000, page 19).

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

trend. The answer to this question will determine whether the strong labor productivity performance of the US economy will extend beyond a typical business cycle horizon of 5-8 years.

5 Industry-Level Results

5.1 The Cross-Industry Distribution of Embodied Technical Progress

Figure 17 plots (and table 6 documents) the cross-industry distribution of embodied technical change (90th percentile, median, mean and 10th percentile) annually, for the whole sample period. Each industry-year observation is weighted by the nominal industry investment share that year. The finer classification with 62 industries is used here. There are two interesting conclusions emerging from Figure 17: first, there is large heterogeneity across industries in the rate of capital-embodied technical progress, as the 90-10 percentile differential averages 6 percent. However, over the years, this gap has remained quite stable which suggests that every industry has benefited from the technological acceleration proportionately.

Another question that we can address with our data is how persistent is the relative position of a given industry in the distribution. For each year, we have divided the distribution into 4 quartiles and we have analyzed the year-by-year transition probabilities across quartiles[35] Table X [not shown] summarizes our findings. For the whole sample, there is quite a lot of mobility for industries, for example the probability of remaining in the same quartile is around 40 percent, except for the bottom quartile showing more persistence. This demonstrates that either there exist large substitution possibilities across investment goods in the production process, or that R&D did not target few industries only in the past 50 years or so. However, the picture changes dramatically in the 1990s, where the diagonal entries increase significantly.

It is easy to reconcile the finding of lower mobility in the 1990s with the "aggregate" nature of the technological acceleration: this is exactly what we would expect from a "general purpose" technology that increases the productivity of the best-practice for all industries in a similar way, reducing

[35]The estimates of the transition probabilities are weighted by the industry investment share in the base year.

therefore the scope for specific innovations that allow certain industries to overtake others in a relatively short time.

The fact that the best practice technology advanced at the same rate for all industries does not mean that the average practice did too: implementation costs can be industry-specific. Figure 18 plots (and table 7 documents) the cross-industry distribution of Hulten's index of technological gap. Although the increase observed in Figure 14 for aggregate data is clear at every point in the distribution, we can also detect a sensible rise in the 90-10 differential: in 1968 industries in the 90th percentile had a technological gap between leading edge machine and average machine of 30 percent and industries in the 10th percentile had a gap of 10 percent. Thirty years later these two numbers are, respectively, 55 percent and 20 percent. We conclude that there are a subset of industries that could exploit better and faster than others the information technology revolutions and invested heavily in new vintages of capital, possibly because of lower implementation costs (i.e., more educated labor force, more flexible organization, etc.). We will see below that these findings are supported by our industry-level growth accounting results.

5.2 "Statistical" Growth Accounting at the Industry Level

In table 8 we report the results of the statistical growth accounting at the industry level based on the following decomposition:

$$\Delta y_{h,t} = \overline{\alpha}_h \Delta l_{h,t} + (1 - \overline{\alpha}_h)\, \Delta \widetilde{k}_{h,t} + (1 - \overline{\alpha}_h)\, \Delta Q^k_{h,t} + z_{h,t}.$$

The quality of capital is the single most important source of growth outside of the trade sectors, where its contribution about equals that from the quantity of capital. The annual average growth rate of the quality of capital is greater in the 1990s in all but one sector.

Perhaps the most striking result is that TFP contracts, sometimes by huge amounts, in nearly every industry. One possible explanation for this puzzling finding is that value-added is systematically mismeasured.[36] This is appealing, after all we have emphasized that it is critically important to quality-adjust capital; the same should go for value-added. But we are

[36] In unreported results, we find that TFP contracts in many industries when we focus on the sources of output growth.

suspicious of this explanation because the industry in which we know quality adjustment is most important, durable goods manufacturing, has positive TFP growth.

This points to an alternative explanation. The TFP contraction may measure the cost of continually integrating improving capital. One reason why this explanation has not been favored is that it would seem to suggest that business in these industries are systematically, over long periods, making losses. While that critique makes sense in some contexts it is less persuasive in our case. In our formulation, firms in the industry are earning profits from the exogenous increase in the quality of capital. From this perspective a better read about how well businesses in the industry are doing is given by the sum of the growth rates of the quality of capital and TFP. This is positive more often than not. And as for the TFP growth in durable goods manufacturing, this growth may reflect disembodied technical change in semiconductors and computers more widely. If that is the case, the disembodied technical change in durable goods manufacturing spurred growth in the quality of capital that was exploited in other industries.

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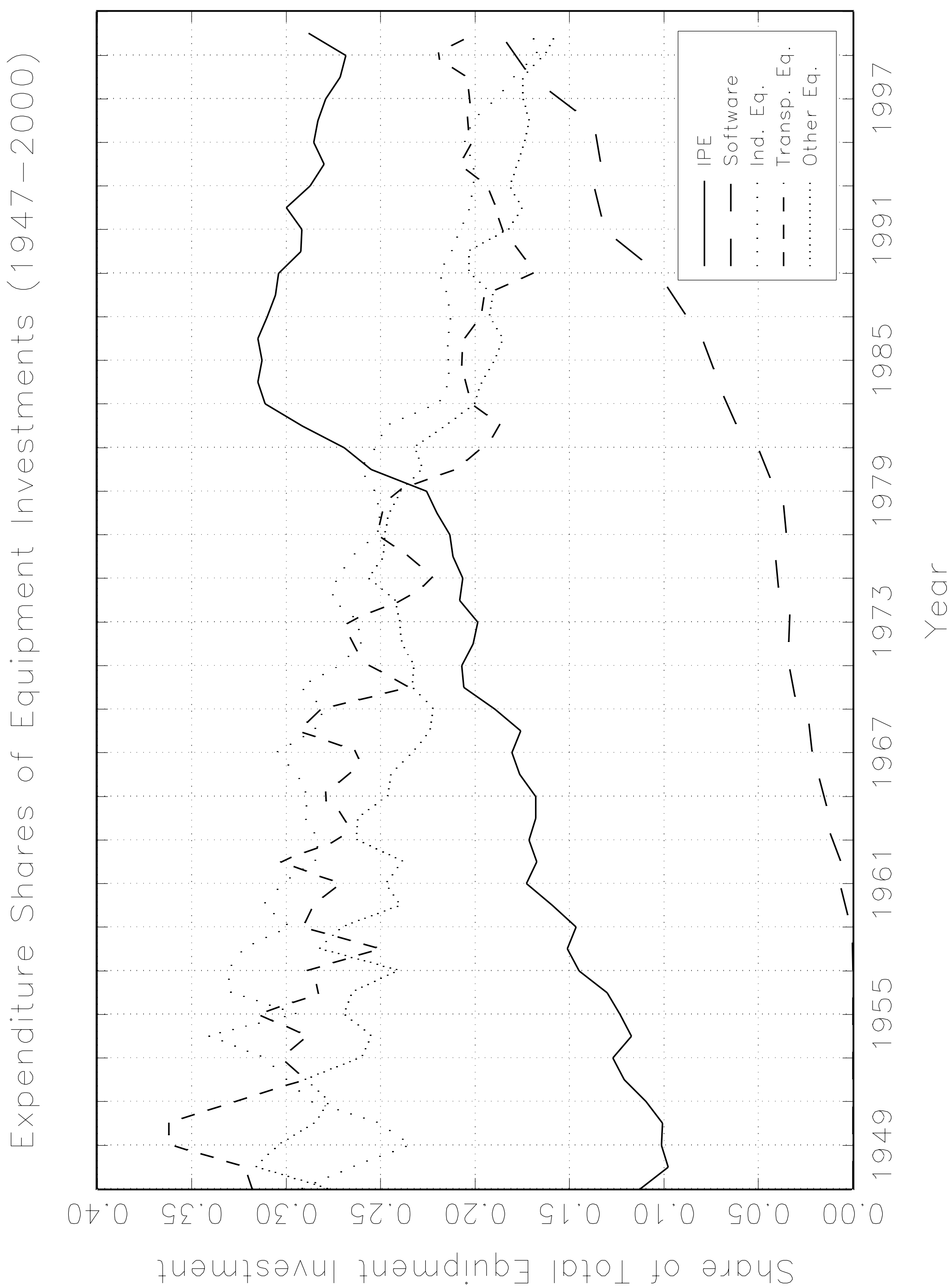

Figure 1: Shares of Nominal Investment

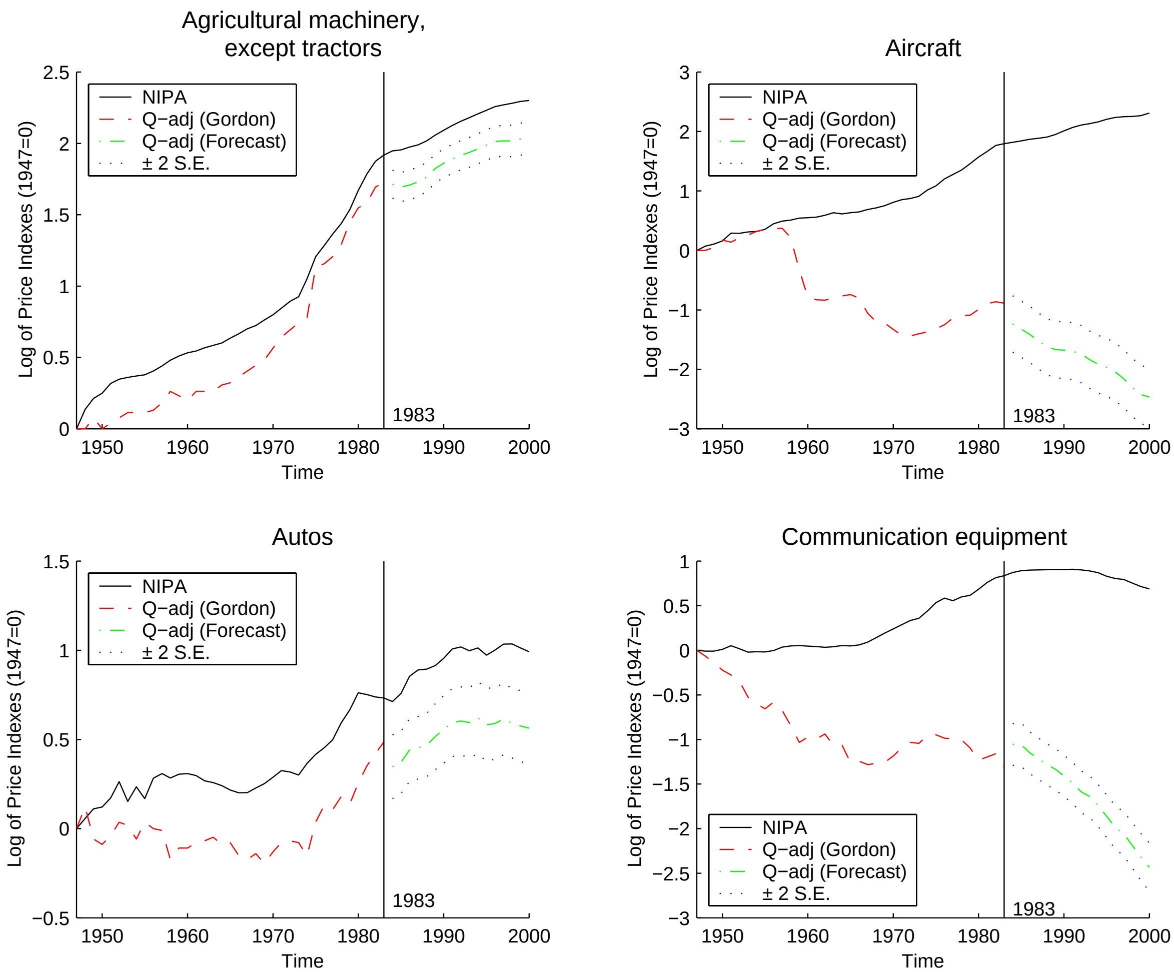

Figure 2: Price Forecasts

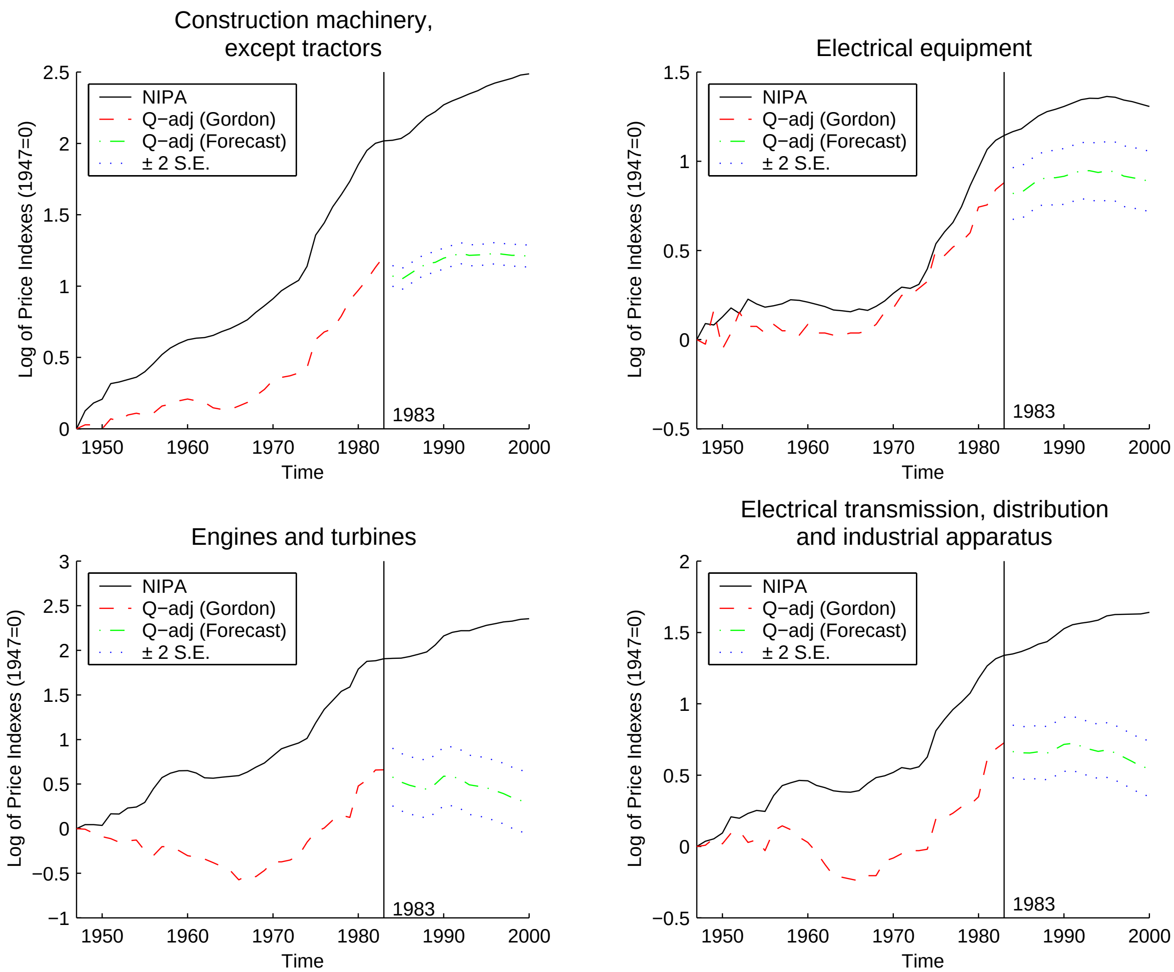

Figure 3: Price Forecasts

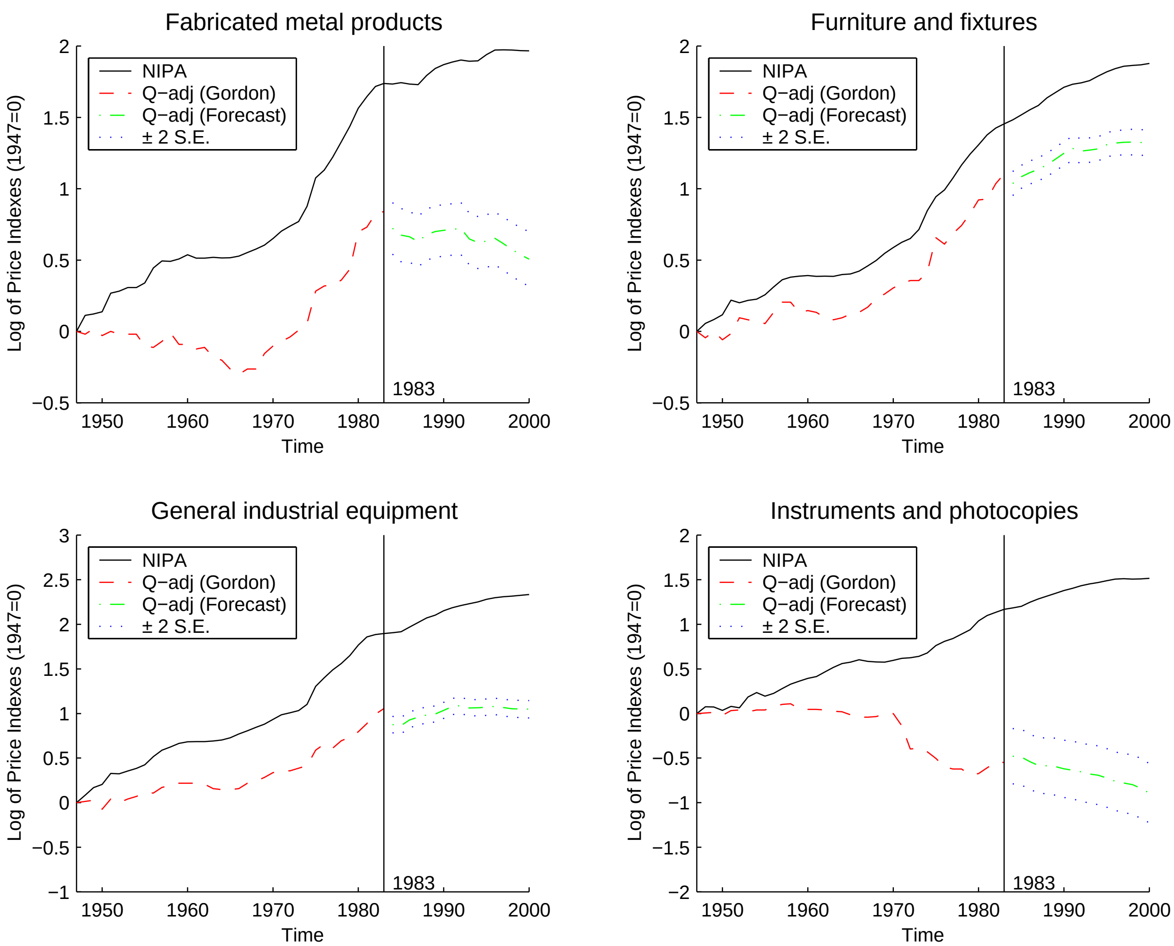

Figure 4: Price Forecasts

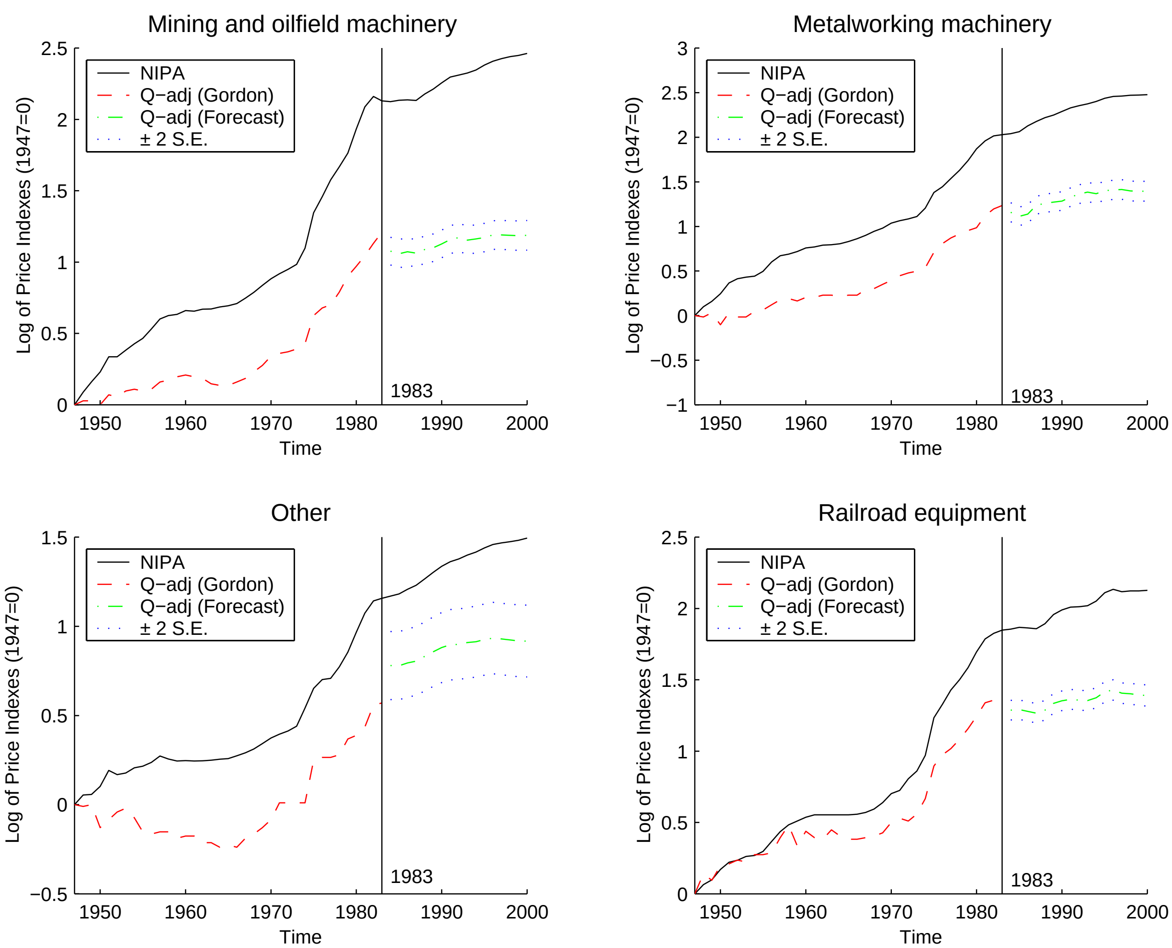

Figure 5: Price Forecasts

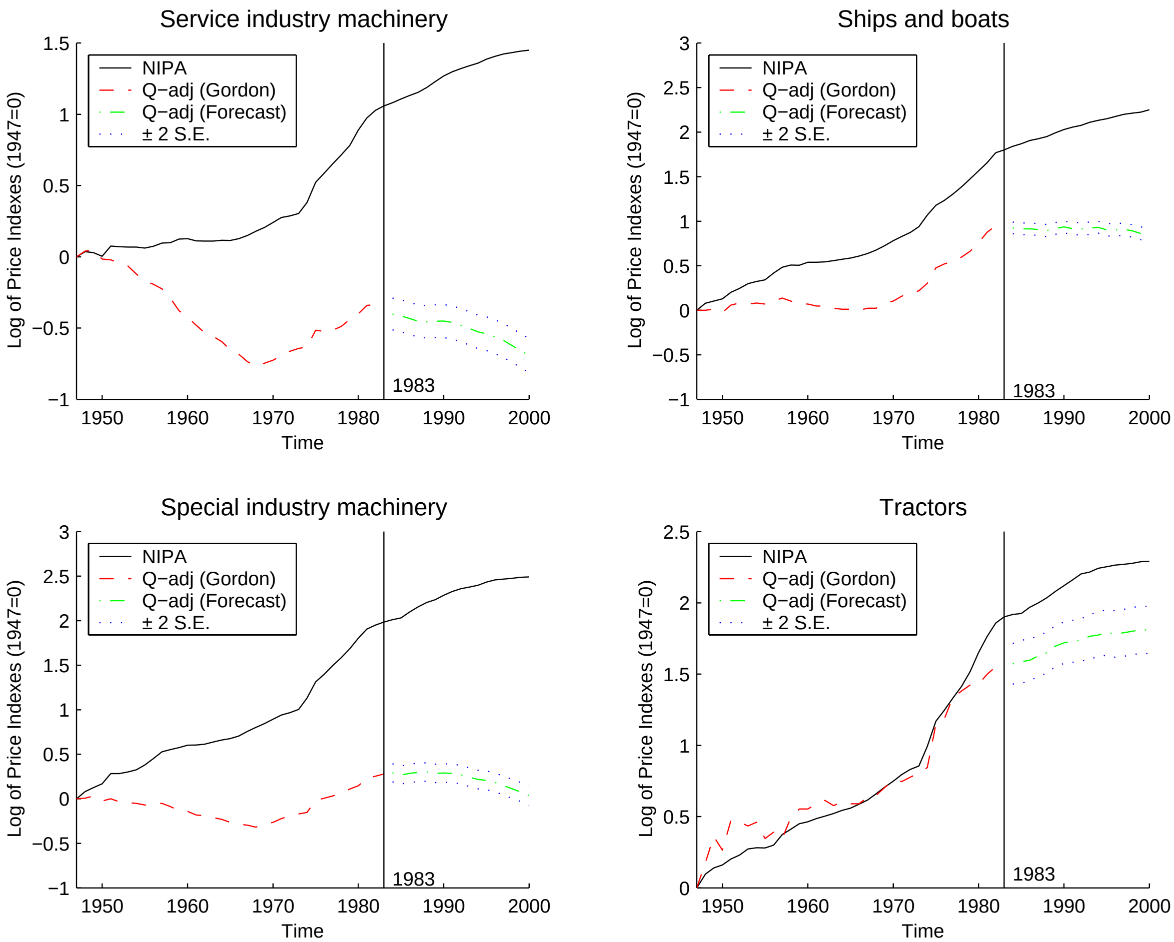

Figure 6: Price Forecasts

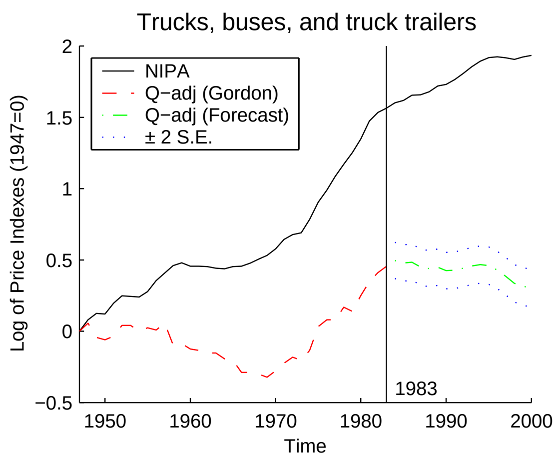

Figure 7: Price Forecasts

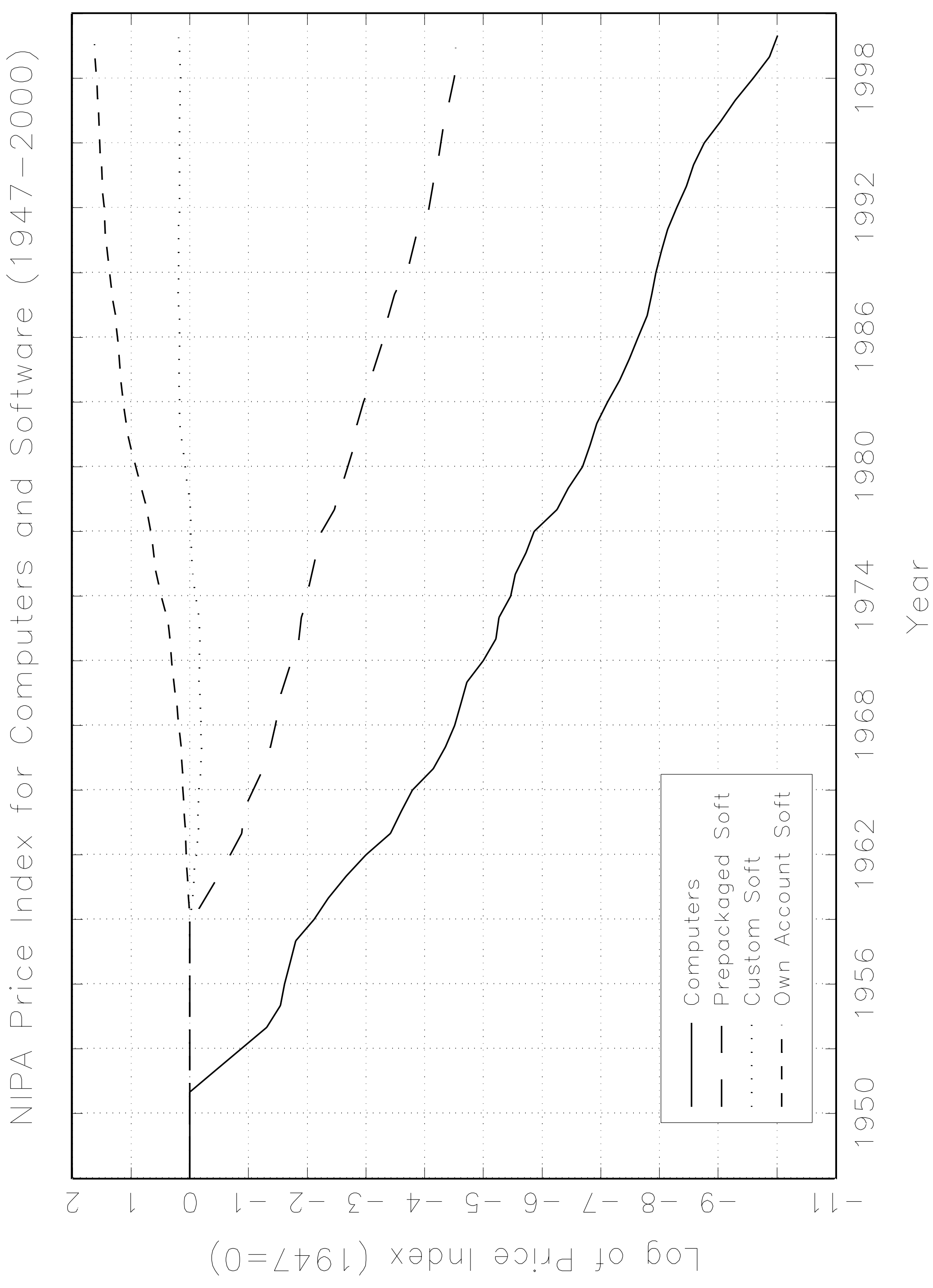

Figure 8: Official NIPA prices for computers and software

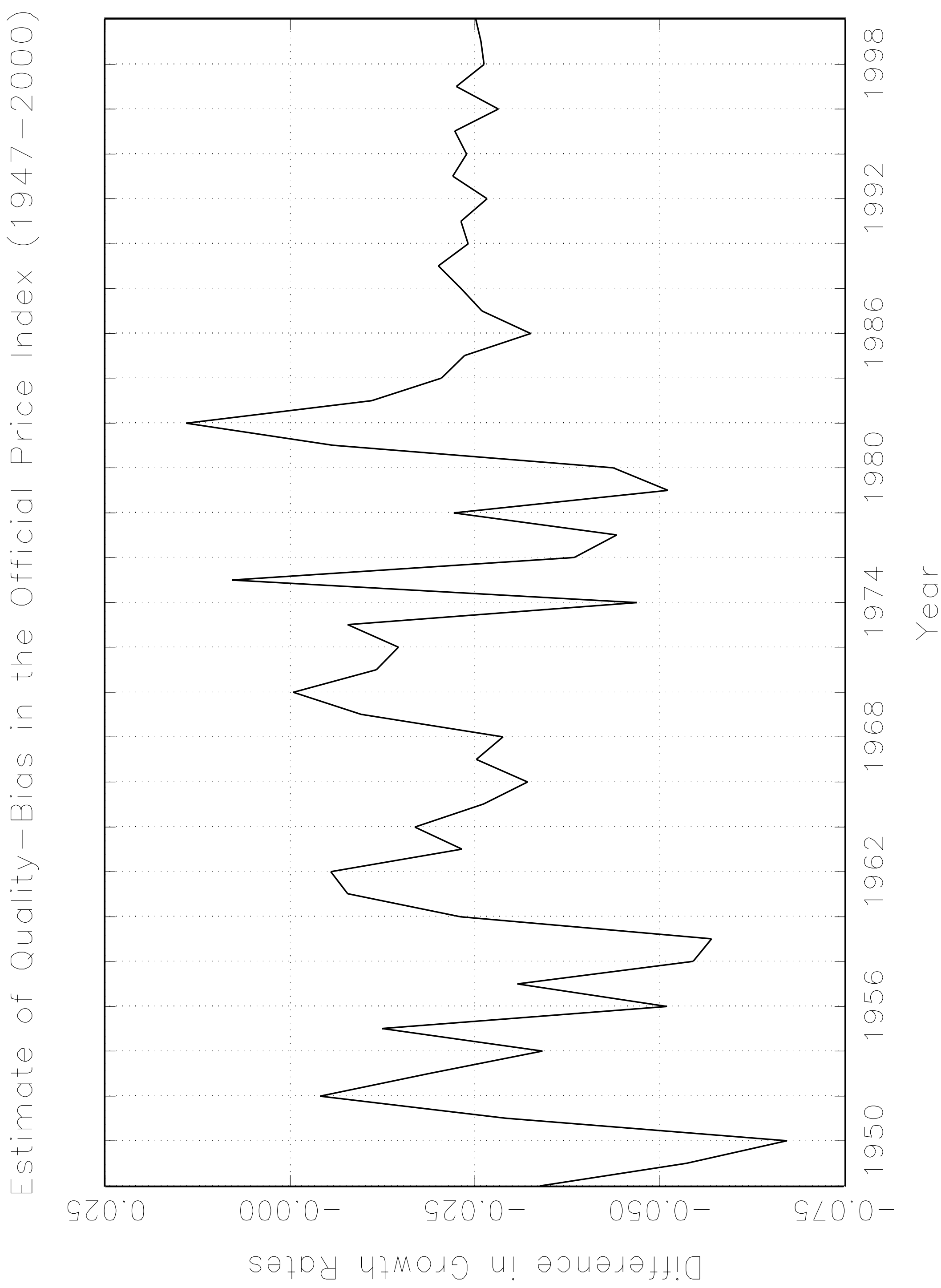

Figure 9: Quality bias in the NIPA official price index for E&S

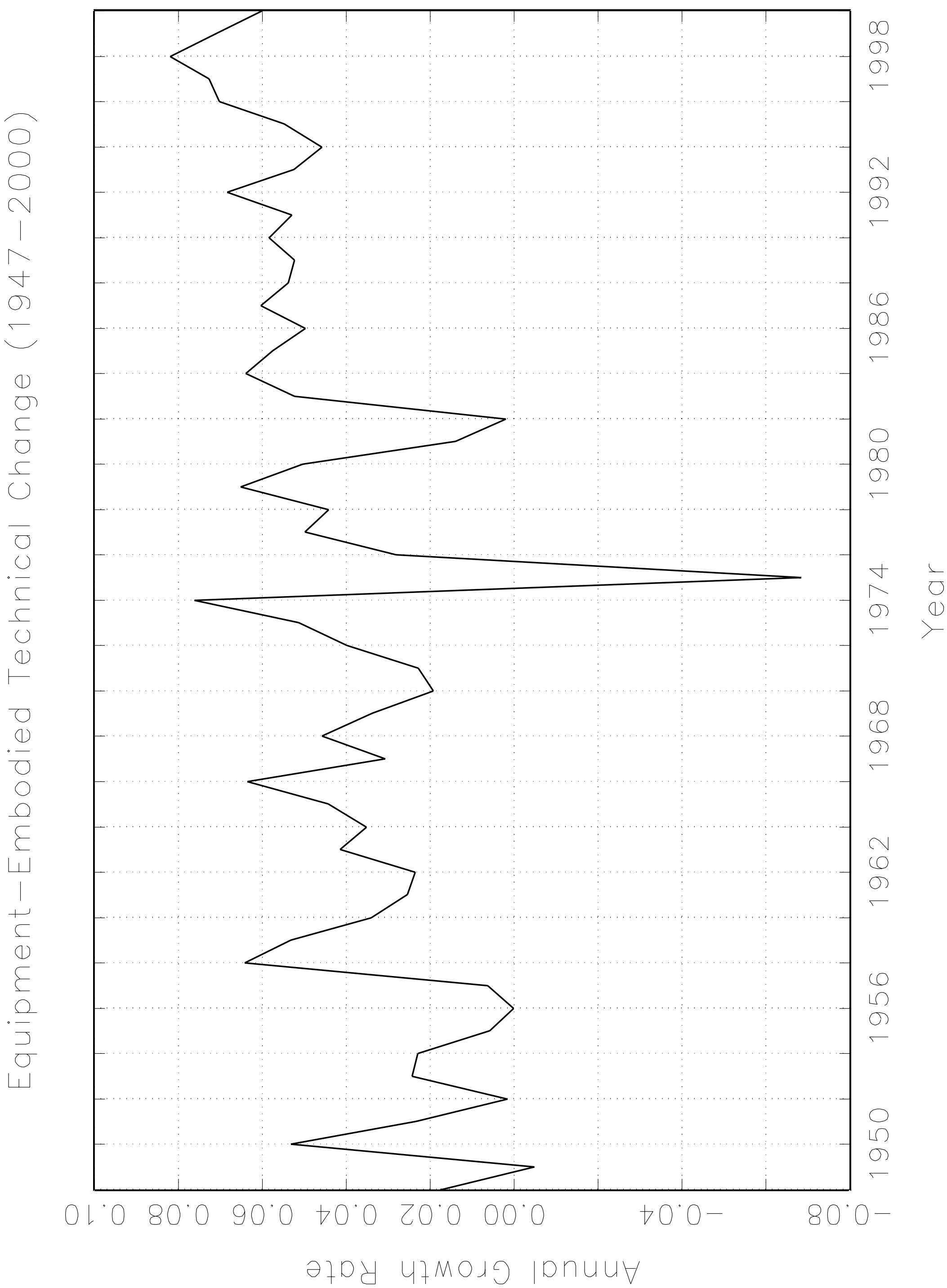

Figure 10: Rate of quality improvement embodied in E&S

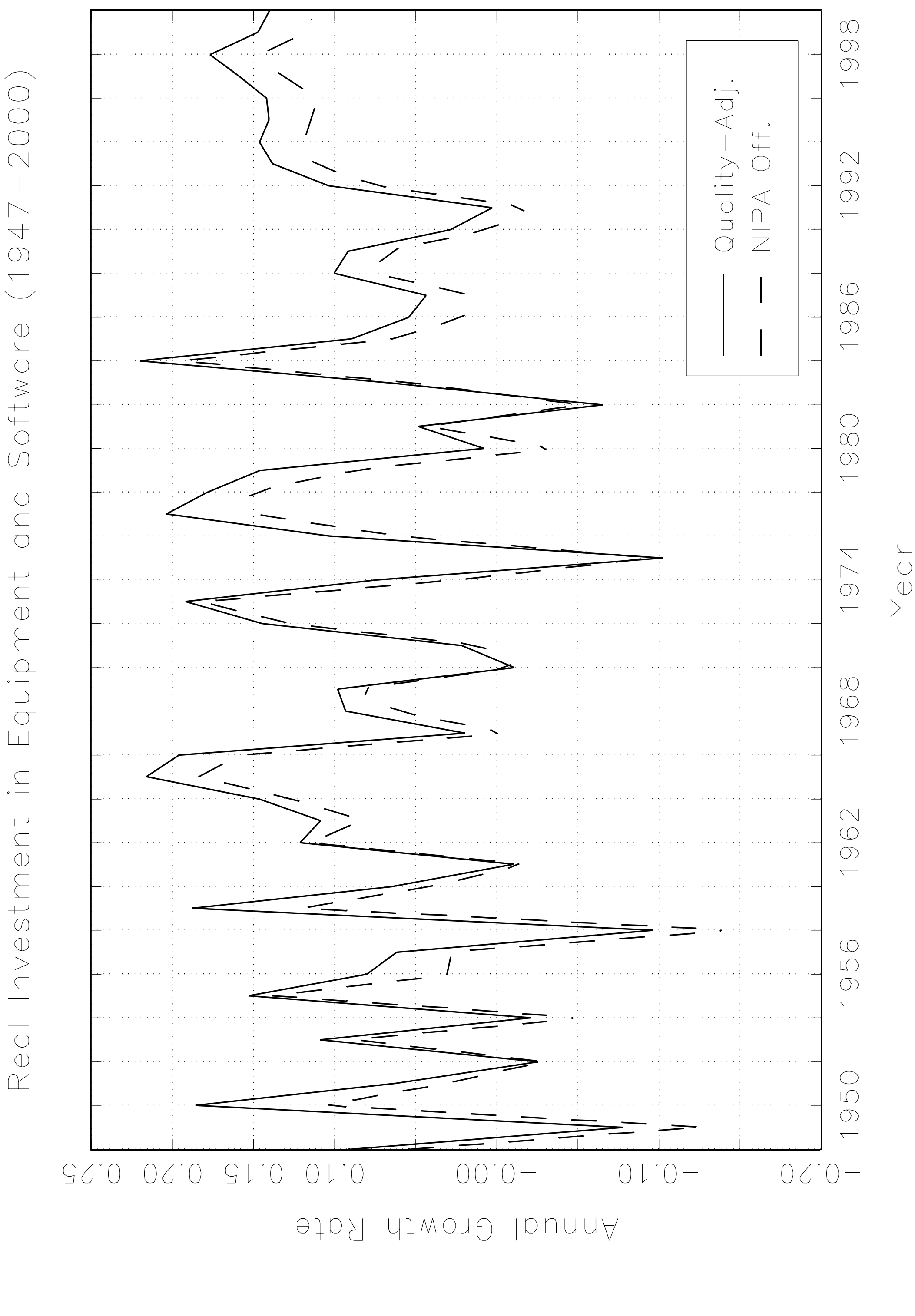

Figure 11: Real Investment in E&S: NIPA official series and quality-adjusted estimate

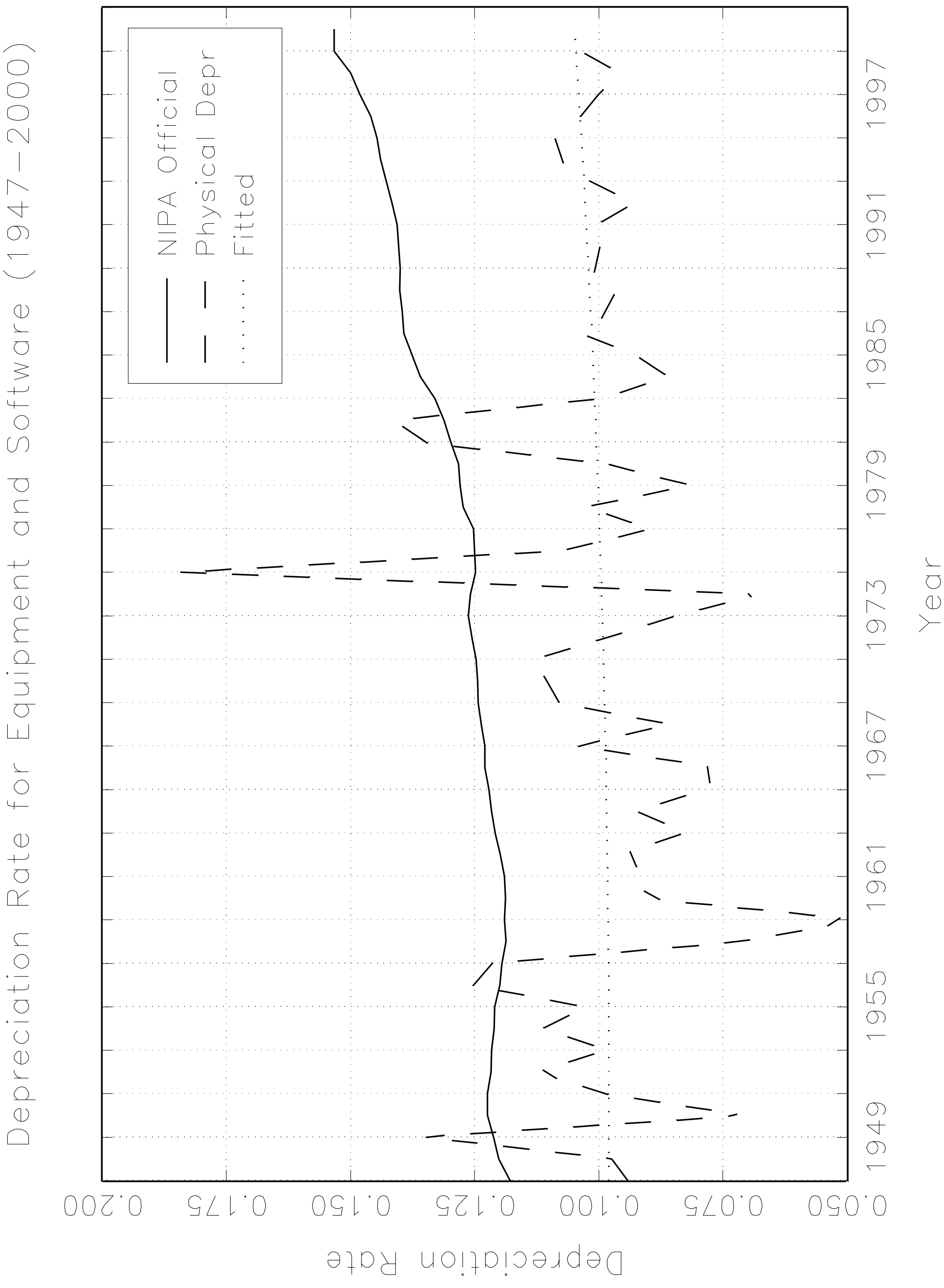

Figure 12: Official economic depreciation and physical decay for E&S

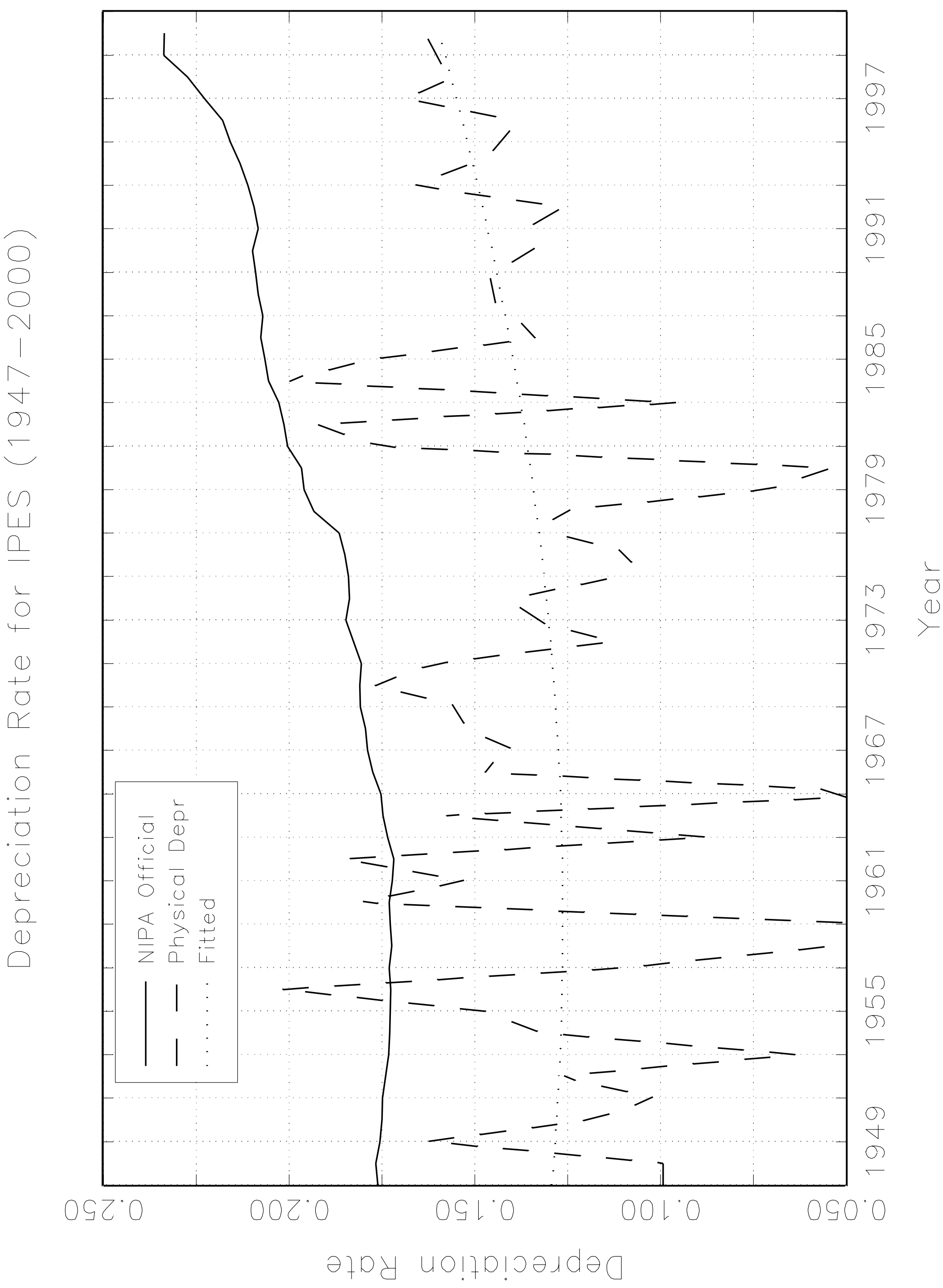

Figure 13: Official economic depreciation and physical decay for IPES

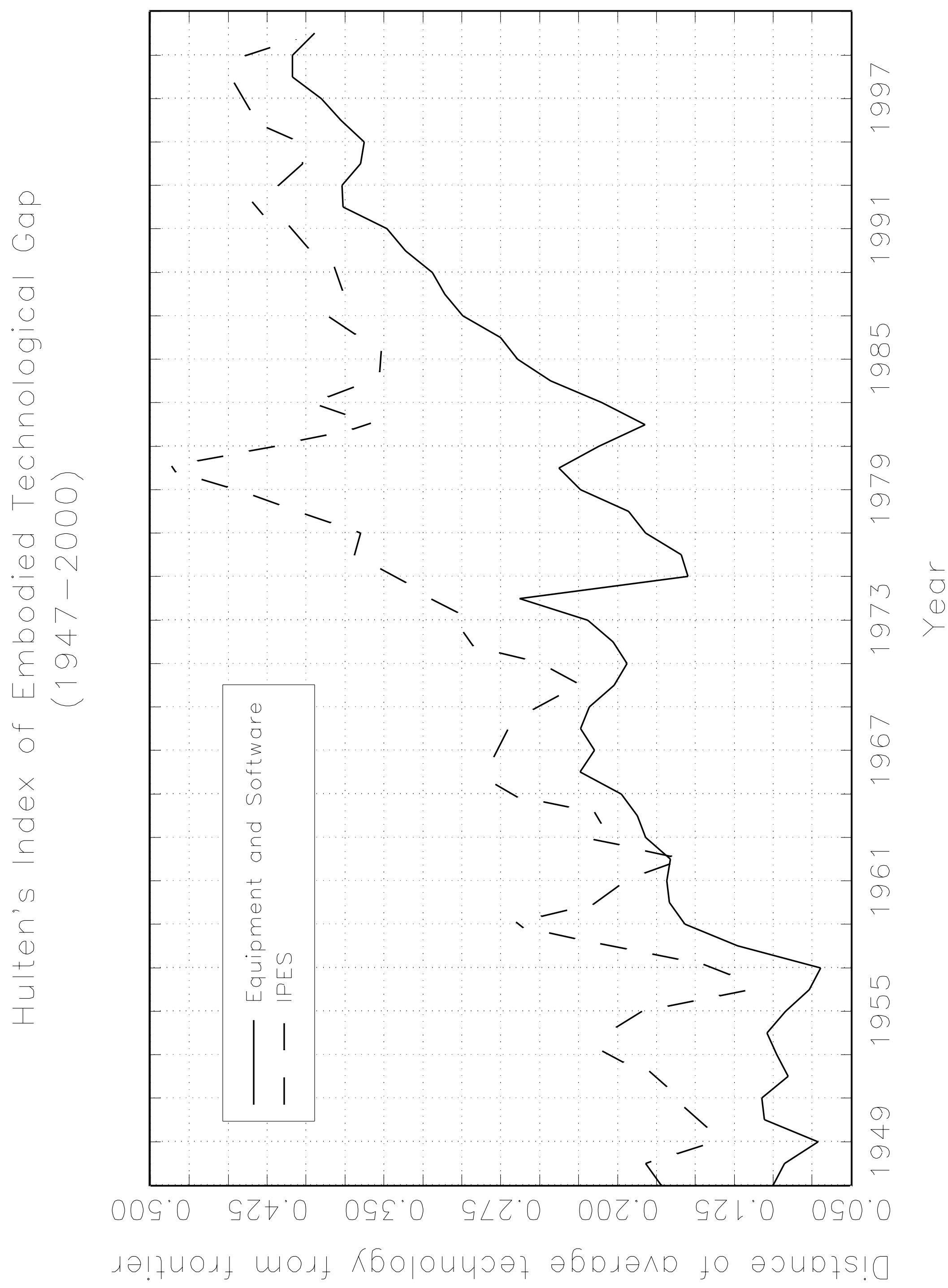

Figure 14: Hulten's index for E&S and IPES

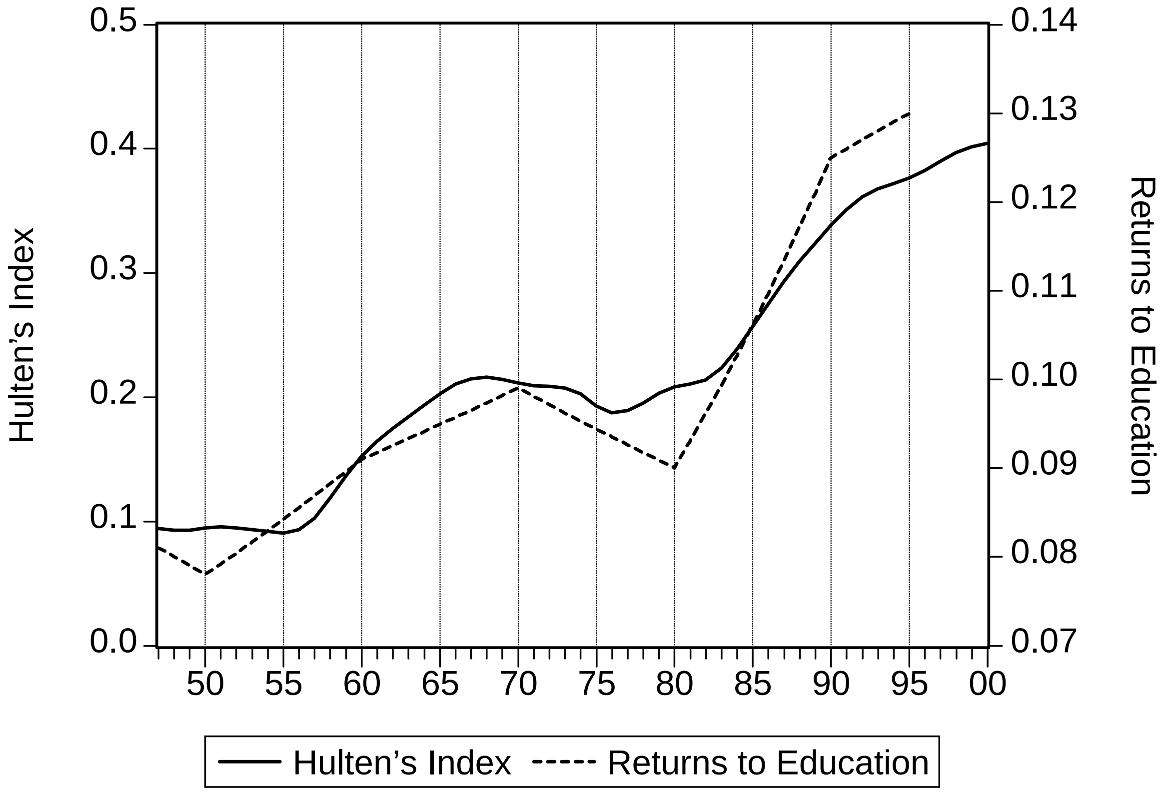

Figure 15: Technological Gap and the Returns to Education

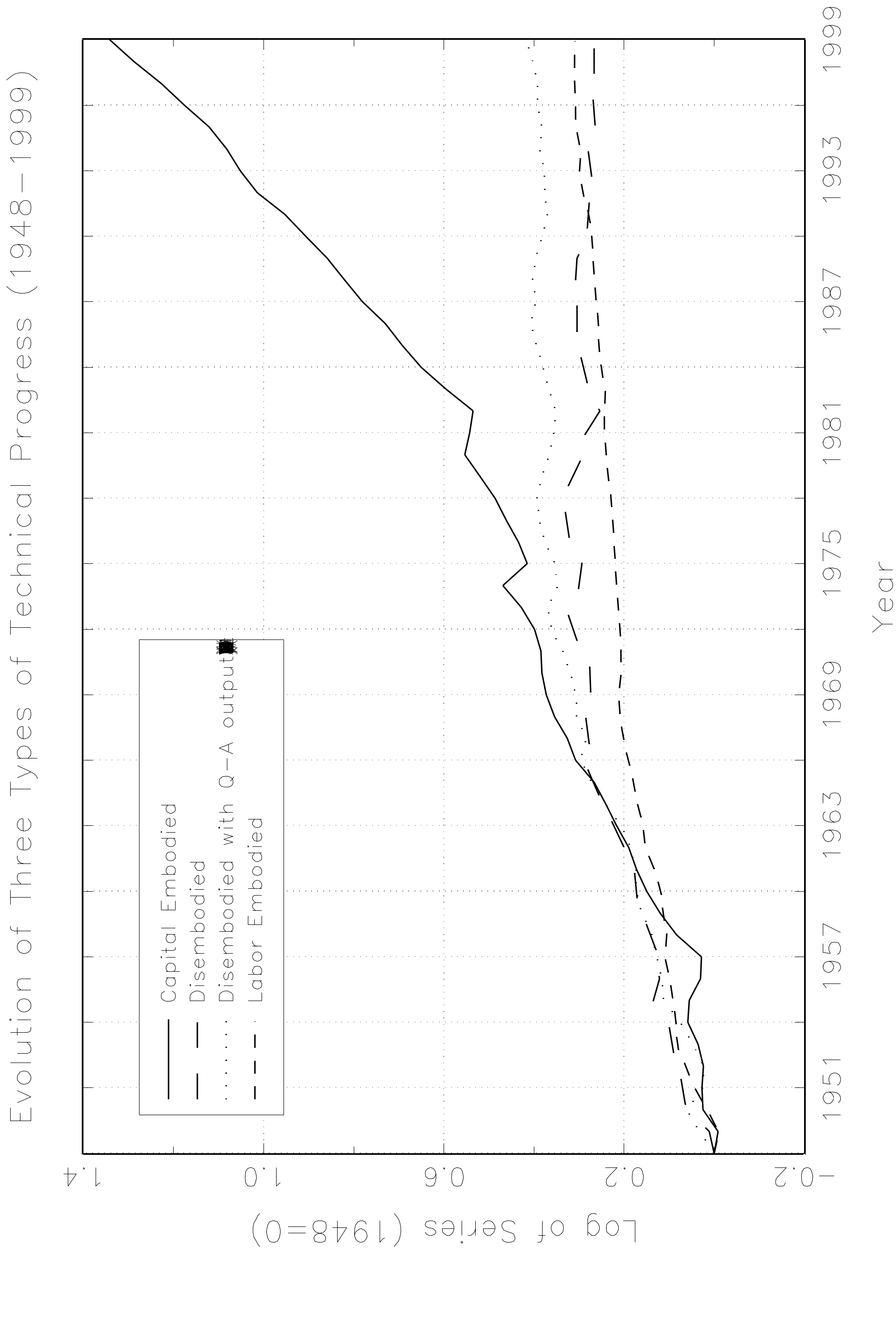

Figure 16: "Equilibrium" growth accounting estimates of technical change embodied in capital, in labor and disembodied

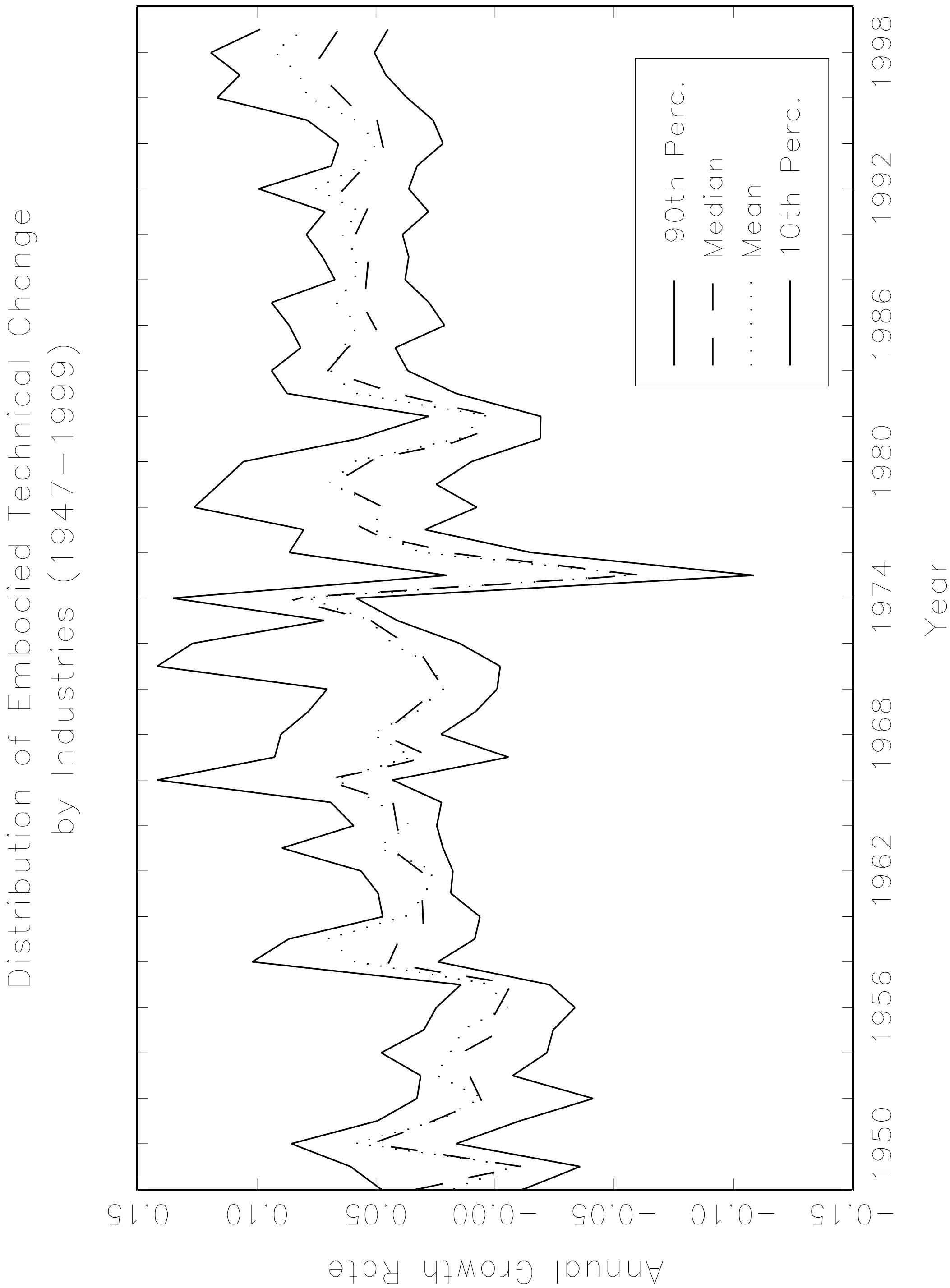

Figure 17: Distribution of rate of quality improvement by industry

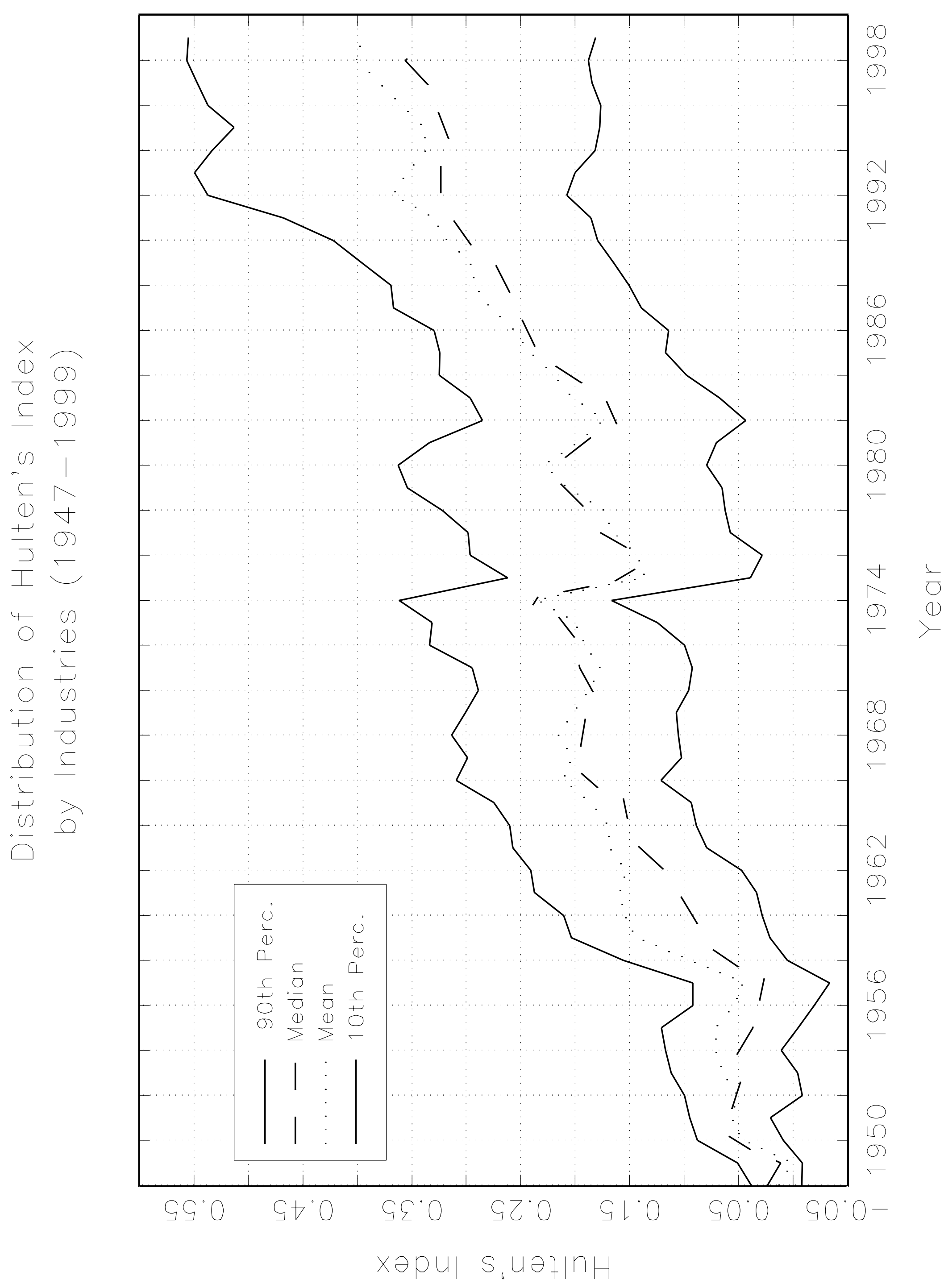

Figure 18: Distribution of Hulten's Index by industry

TABLE 1 (part 1 of 3) - Regression Results for the 21 Quality-adjusted Price Indexes

Explanatory Variables	(1) Agric	(2) Aircrafts	(3) Auto	(4) Comm	(5) Constr	(6) Electr	(7) Engines	(8) ETDIA
NIPA Official Price $^{(*)}$	1.71	2.37	0.84	1.68	0.95	1.23	1.48	1.40
	(14.16)	(8.40)	(4.99)	(10.33)	(25.56)	(7.65)	(9.86)	(13.39)
NIPA Official Price$_{-1}$ $^{(*)}$	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
NIPA Official Price$_{-2}$ $^{(*)}$	-0.69	-	-	-	-	-0.49	-	-
	(-5.18)	-	-	-	-	(-2.53)	-	-
NIPA Official Price$_{-3}$ $^{(*)}$	-	-	0.42	-	-	-	-	-
	-	-	(2.16)	-	-	-	-	-
GDP Growth	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
GDP Growth$_{-1}$	-	-	-	0.01	-0.01	-	-	-
	-	-	-	(1.57)	(-2.82)	-	-	-
GDP Growth$_{-2}$	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
Constant	-3.40	-3.89	-4.70	-5.47	-2.55	-2.71	-3.26	-4.23
	(-62.78)	(-5.84)	(-8.51)	(-9.19)	(-30.97)	(-16.00)	(-9.77)	(-13.62)
Time Trend*100	-	-14.97	-0.85	-6.65	-1.91	-	-6.06	-3.30
	-	(-11.91)	(-3.39)	(-15.82)	(-9.86)	-	(-7.83)	(-9.42)
Adjusted R^2	0.99	0.89	0.79	0.91	0.99	0.95	0.77	0.87

Note: t-statistics are in parethesis, $^{(*)}$ denotes logs, there are 37 observations for each estimated equation and all price indexes are in logs.

TABLE 1 (part 2 of 3) - Regression Results for the 21 Quality-adjusted Price Indexes

Explanatory Variables	(9) FMP	(10) Furniture	(11) GIE	(12) Ins-Pho	(13) Mine	(14) MWM	(15) Other Eq	(16) Rail
NIPA Official Price $^{(*)}$	1.23	0.60	0.76	-0.57	0.73	0.72	1.10	0.86
	(15.07)	(3.02)	(13.60)	(-1.14)	(18.74)	(3.14)	(10.28)	(29.33)
NIPA Official Price$_{-1}$ $^{(*)}$	-	0.42	-	-	-	0.72	-	-
	-	(2.07)	-	-	-	(1.76)	-	-
NIPA Official Price$_{-2}$ $^{(*)}$	-	-	-	1.36	-	-0.74	-	-
	-	-	-	(2.43)	-	(-3.13)	-	-
NIPA Official Price$_{-3}$ $^{(*)}$	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
GDP Growth	-	-0.01	-0.01	-	-	-	-	-
	-	(-2.91)	(-2.00)	-	-	-	-	-
GDP Growth$_{-1}$	-0.01	-	-0.01	-	-0.01	-	-	-
	(-1.81)	-	(-3.65)	-	(-2.12)	-	-	-
GDP Growth$_{-2}$	-	-	-	-	-	-0.01	-	-
	-	-	-	-	-	(-3.44)	-	-
Constant	-3.40	-3.25	-2.22	-1.70	-2.10	-2.27	-3.67	-2.57
	(-15.55)	(-25.20)	(-16.25)	(-1.24)	(-23.70)	(-45.13)	(-11.06)	(-36.65)
Time Trend*100	-3.13	-0.91	-1.08	-4.57	-0.85	-	-1.37	-0.82
	(-8.84)	(-5.16)	(-4.00)	(-3.42)	(-4.07)	-	(-4.47)	(-5.65)
Adjusted R^2	0.93	0.99	0.98	0.77	0.98	0.99	0.86	0.99

TABLE 1 (part 3 of 3) - Regression Results for the 21 Quality-adjusted Price Indexes

Explanatory Variables	(17) Serv	(18) Ships	(19) Spec	(20) Tract	(21) Trucks
NIPA Official Price $^{(*)}$	1.22	1.51	0.99	1.25	1.15
	(22.30)	(8.48)	(18.45)	(6.86)	(18.21)
NIPA Official Price$_{-1}$ $^{(*)}$	-	0.55	-	-	-
	-	(1.83)	-	-	-
NIPA Official Price$_{-2}$ $^{(*)}$	-	-0.88	-	-0.55	-
	-	(-4.26)	-	(-2.70)	-
NIPA Official Price$_{-3}$ $^{(*)}$	-	0.01	-	-	-
	-	(2.97)	-	-	-
GDP Growth	-	-	-	-	-
	-	-	-	-	-
GDP Growth$_{-1}$	-	-	-	0.01	-
	-	-	-	(2.66)	-
GDP Growth$_{-2}$	-	-	-	-	-
	-	-	-	-	-
Constant	-3.16	-3.24	-2.01	-2.29	-2.99
	(-18.96)	(-34.54)	(-17.83)	(-28.89)	(-17.82)
Time Trend*100	-4.64	-3.16	-4.58	-	-3.65
	(-29.06)	(-18.63)	(-16.52)	-	(-14.75)
Adjusted R^2	0.96	0.99	0.91	0.98	0.91

Note: t-statistics are in parethesis, $^{(*)}$ denotes logs, there are 37 observations for each estimated equation and all price indexes are in logs.

Table 2 – Constant-Quality Capital Growth (1948-2000)

	48-00	47-60	61-70	71-80	81-90	91-00
Δk_e^*	0.088	0.091	0.089	0.087	0.075	0.100
Δk_e	0.058	0.056	0.059	0.061	0.046	0.068
Δk_{ipes}^*	0.163	0.137	0.165	0.179	0.172	0.163
Δk_{ipes}	0.123	0.086	0.132	0.137	0.132	0.133

Table 3– Annual Rates of Embodied Technical Change by Asset Type

	48-00	48-60	61-70	71-80	81-90	91-00
Equipment and Software	.040	.023	.036	.036	.046	.063
Information Processing Equipment and Software	.074	.043	.063	.065	.082	.078
Computers and Peripheral equipment	.235$^{(*)}$	-	.266	.265	.182	.225
Prepackaged Software	.153$^{(*)}$	-	.157	.181	.158	.099
Custom Software	.038$^{(*)}$	-	.040	.044	.036	.026
Own Account Software	.002$^{(*)}$	-	.005	.003	.001	.003
Communication equipment	.087	.096	.051	.073	.085	.129
Instruments and Photocopies	.056	.017	.034	.135	.050	.054
Office and Accounting equipment	.024	.000	.021	.053	.031	.024
Industrial Equipment	.030	.031	.017	.028	.039	.033
Fabricated Metal Products	.027	.028	.031	.012	.044	.047
Engines and Turbines	.032	.044	.037	.017	.034	.059
Metalworking Machinery	.009	.005	.011	.009	.008	.016
Special Industry Machinery, n.e.c.	.038	.032	.042	.027	.036	.052
General Industrial equipment	.016	.004	.018	.022	.013	.026
Electrical Transm., Distr. and Industr.	.026	.018	.041	.025	.007	.044
Transportation Equipment	.030	.044	.020	.022	.035	.026
Trucks, Buses, and Truck Trailers	.033	.030	.045	.015	.033	.040
Autos	.025	.029	.032	.030	.006	.026
Aircraft	.079	.081	.084	.035	.091	.106
Ships and Boats	.021	.015	.026	.003	.030	.034
Railroad Equipment	.010	.013	.023	.006	.031	.023
Other Equipment	.019	.018	.005	.022	.028	.023
Furniture and Fixtures	.011	.009	.014	.006	.008	.020
Tractors	.003	.022	.009	.001	.020	.018
Agricultural Machinery	.001	.005	.007	.030	.016	.009
Construction Machinery	.013	.005	.016	.005	.016	.026
Mining and Oilfield Machinery	.014	.005	.016	.005	.024	.021
Service Industry Machinery	.049	.053	.060	.036	.046	.051
Electrical Equipment, n.e.c.	.020	.014	.027	.011	.024	.030
Other Equipment	.024	.034	.020	.021	.019	.023

Note: $^{(*)}$ denotes the period 1960-2000. Each entry is the average over the period. Rates of technical change embodied in asset j is computed as the inverse of the growth rate of the quality-adjusted price of asset j relative to the price of consumption.

Table 4: Statistical growth accounting (1948-1999)

	Output *unadjusted* for quality						Output *adjusted* for quality					
	48-99	48-60	61-70	71-80	81-90	91-99	48-99	48-60	61-70	71-80	81-90	91-99
GDP growth	3.718	3.675	4.338	3.639	3.394	3.532	4.014	3.687	4.821	3.893	3.599	4.148
Contribution of Capital (k)	.536	.411	.487	.597	.602	.642	.497	.410	.438	.558	.568	.547
Quantity of Capital ($\tilde{k}$)	.325	.229	.306	.428	.361	.332	.301	.228	.275	.400	.341	.283
Quantity of IT Capital ($\tilde{k}_{\text{ipes}}$)	.055	.026	.039	.049	.060	.049	.051	.026	.035	.046	.057	.042
Quantity of Other Capital ($\tilde{k}_{\text{other}}$)	.270	.203	.267	.379	.301	.283	.250	.202	.240	.354	.284	.241
Quality of Capital (Q)	.211	.182	.181	.169	.241	.310	.196	.181	.163	.158	.227	.294
Quality of IT Capital (Q_{ipes})	.060	.014	.027	.062	.090	.124	.056	.014	.024	.058	.085	.118
Quality of Other Capital (Q_{other})	.151	.168	.154	.107	.151	.186	.140	.167	.139	.10	.142	.176
Contribution of Labor (l)	.323	.200	.290	.342	.413	.419	.299	.200	.261	.320	.389	.397
Quantity of Labor (n)	.219	.029	.158	.186	.351	.345	.203	.029	.142	.174	.331	.327
Quality of Labor (h)	.104	.171	.132	.156	.062	.074	.096	.170	.119	.146	.058	.070
Aggregate TFP (z)	.141	.389	.224	.061	-.015	-.061	.204	.390	.301	.122	0.04	.056

Note: The contribution of each component is defined as the ratio between the share-weighted real growth rate of that component and real GDP growth. The aggregate share of labor (capital) is constant at .64 (.36) over the sample period. To compute the contribution of IT goods we used the Tornquist decomposition in equation (**??**).

Table 5: Cycle and Trend in the Recent Productivity Surge

	Total	Cycle		Trend	
		λ=6.25	λ=100	λ=6.25	λ=100
Total	1.00	.315	.889	.685	.111
Capital Deepening	.423	.170	.433	.253	-.100
Quantity of Capital	-.238	.077	.125	-.315	-.363
IT Capital	-.040	.051	.136	-.090	-.175
Other Capital	-.199	.026	-.009	-.225	-.188
Quality of Capital	.661	.093	.308	.568	.353
IT Capital	.286	.058	.204	.228	.082
Other Capital	.375	.035	.104	.340	.271
Labor Quality	-.297	-.124	-.294	-.173	-.003
Aggregate TFP	.875	.270	.750	.605	.125

Note: The labor productivity acceleration is .087, computed comparing average annual productivity growth in 1995-1999 to 1973-1995. The cyclical component is extracted from each series through the Hodrick-Prescott filter. The data have annual frequency, so both a value of λ=100 and a value of λ=6.25 are used (see the main text for an explanation). The contribution of the various components reported in each row is defined as the ratio between the share-weighted real growth rate of that component and real GDP growth (quality-adjusted). The aggregate share of labor (capital) is constant at .64 (.36) over the sample period. To compute the contribution of IT goods we used the Tornquist decomposition in equation (10).

Table 6 - Embodied Technical Change by Industry

Industry	48-99		48-60		61-70		71-80		81-90		91-99	
	ETC	Share	ETC	Share	ETC	Share	ETC	Share	ETC	Share	ETC	Share
1 Agriculture	0.011	0.080	0.008	0.124	0.011	0.087	-0.008	0.084	0.023	0.044	0.024	0.043
2 Extractive	0.024	0.033	0.009	0.030	0.024	0.032	0.015	0.039	0.035	0.040	0.044	0.022
3 Construction	0.022	0.037	0.011	0.052	0.024	0.047	0.010	0.037	0.027	0.020	0.045	0.024
4 Durable Manufacturing	0.035	0.139	0.013	0.148	0.032	0.155	0.039	0.145	0.041	0.129	0.057	0.115
5 Nondurable Manufacturing	0.039	0.119	0.024	0.129	0.039	0.127	0.040	0.121	0.041	0.107	0.056	0.108
6 Transport and Utilities	0.040	0.156	0.023	0.184	0.049	0.162	0.022	0.155	0.046	0.143	0.067	0.123
7 Communications	0.077	0.079	0.076	0.062	0.052	0.086	0.073	0.086	0.081	0.082	0.109	0.085
8 Wholesale Trade	0.055	0.058	0.026	0.035	0.048	0.045	0.060	0.054	0.064	0.080	0.088	0.086
9 Retail Trade	0.043	0.057	0.033	0.067	0.043	0.056	0.038	0.050	0.049	0.056	0.059	0.054
10 FIRE	0.056	0.131	0.034	0.088	0.048	0.097	0.070	0.117	0.058	0.177	0.080	0.195
11 Other Services	0.050	0.111	0.029	0.081	0.046	0.106	0.053	0.111	0.062	0.121	0.068	0.145

Table 7 - Hulten's Technological Gap by Industry

Industry	48-99	48-60	61-70	71-80	81-90	91-99
	ETC	ETC	ETC	ETC	ETC	ETC
1 Agriculture	0.051	0.015	0.067	-0.008	0.064	0.134
2 Extractive	0.118	0.027	0.097	0.075	0.142	0.295
3 Construction	0.094	0.031	0.098	0.064	0.103	0.203
4 Durable Manufacturing	0.177	0.042	0.129	0.173	0.245	0.355
5 Nondurable Manufacturing	0.228	0.088	0.219	0.240	0.272	0.379
6 Transport and Utilities	0.283	0.056	0.320	0.280	0.301	0.556
7 Communications	0.410	0.240	0.319	0.274	0.568	0.734
8 Wholesale Trade	0.183	0.069	0.154	0.188	0.230	0.320
9 Retail Trade	0.185	0.092	0.206	0.177	0.213	0.273
10 FIRE	0.200	0.084	0.179	0.242	0.233	0.309
11 Other Services	0.182	0.059	0.161	0.211	0.247	0.280

TABLE 8: Sources of Growth at the Industry Level (1977-99)

Annual average share-weighted growth rate (%)	1977-99	1977-89	1990-99
Source			
Industry: Durable Goods Manufacturing			
Value-Added	2.544	2.602	2.639
Labor	-0.127	-0.105	0.029
Capital			
Quantity of Capital	0.656	0.703	0.546
Quality of Capital	0.949	0.780	1.070
TFP	1.066	1.224	0.994
Industry: Non-Durable Goods Manufacturing			
Value-Added	-0.308	-0.267	0.043
Labor	-0.183	-0.027	-0.362
Capital			
Quantity of Capital	0.976	0.972	0.858
Quality of Capital	1.395	1.159	1.535
TFP	-2.496	-2.370	-1.989
Industry: Transportation and Utilities			
Value-Added	2.088	1.207	3.101
Labor	0.834	0.795	0.821
Capital			
Quantity of Capital	1.131	1.294	0.865
Quality of Capital	1.566	1.301	1.760
TFP	-1.444	-2.183	-0.345
Industry: Communications			
Value-Added	4.837	4.355	4.855
Labor	0.448	0.171	0.649
Capital			
Quantity of Capital	2.480	2.643	2.063
Quality of Capital	3.641	3.013	4.101
TFP	-1.732	-1.472	-1.958

Annual average share-weighted growth rate (%)	1977-99	1977-89	1990-99
Source			
Industry: Wholesale Trade			
Value-Added	5.269	4.775	6.027
Labor	0.951	1.229	0.639
Capital			
Quantity of Capital	2.366	2.883	1.593
Quality of Capital	2.451	2.144	2.651
TFP	-0.498	-1.481	1.144
Industry: Retail Trade			
Value-Added	3.688	3.310	4.237
Labor	1.412	1.683	1.030
Capital			
Quantity of Capital	1.421	1.517	1.164
Quality of Capital	1.455	1.383	1.397
TFP	-0.601	-1.274	0.646
Industry: FIRE			
Value-Added	1.344	-2.550	5.307
Labor	0.519	0.719	0.234
Capital			
Quantity of Capital	3.471	4.205	2.166
Quality of Capital	3.420	3.402	3.114
TFP	-6.067	-10.876	-0.207
Industry: Other Services			
Value-Added	3.322	4.115	2.082
Labor	2.944	3.120	2.421
Capital			
Quantity of Capital	1.235	1.210	1.165
Quality of Capital	1.511	1.347	1.568
TFP	-2.368	-1.562	-3.074