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# Changing Technology Trends, Transition Dynamics and Growth Accounting

Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

# Changing Technology Trends, Transition Dynamics and Growth Accounting

Michael R. Pakko*

Federal Reserve Bank of St. Louis
P.O. Box 442
St. Louis, MO 63166

(314) 444-8564
pakko@stls.frb.org

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## *Abstract*

The technology growth trends that underlie recent productivity patterns are investigated in a framework that incorporates investment-specific technological progress. Structural-break tests and regime-shifting models reveal the presence of a downward shift in TFP growth in the late 1960s and an upward shift in investment-specific technology growth in the mid-1980s. In both cases, these breaks precede the generally-recognized dates of labor productivity growth shifts. Simulations of technology growth shocks in a basic neoclassical model show that induced patterns of capital accumulation are generally consistent with the observed lags between technological advances and changes in productivity growth.

* The views expressed in this paper are those of the author and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System or the Board of Governors.

## Changing Technology Trends, Transition Dynamics, and Growth Accounting

The increase in productivity growth since the mid-1990s has proven to be persistent and durable. Having continued through a recession and into the current expansion, the acceleration of the late 1990s provides a counterpoint to the productivity slowdown of the early 1970s. Because the role of new technologies is commonly seen as central to the emergence of increased productivity growth, research on this growth resurgence has focused on advances in information-technology (IT), which is often characterized as being "capital-embedded," or "investment-specific" in its application.

A consensus has emerged that dates the increase in productivity growth in the mid-1990s.[1] However, the rapid pace of innovation in IT had been recognized long before that time. Indeed, the famous "Solow productivity paradox," that we "see the computer age everywhere but in the productivity statistics" dates to nearly a decade earlier.[2]

In this paper, I use a dynamic neoclassical growth framework to examine two prominent, specific changes in technology growth trends of the past half-century, along with subsequent patterns of capital accumulation and productivity growth. Applying the approach of Greenwood, Hercowitz and Krusell (2000) to measure Hicks-neutral and investment-specific technology as two independent sources of exogenous growth, the empirical evidence presented here suggests a negative structural break in neutral technology growth in the late 1960s and a partially offsetting positive break in investment-specific technology growth in the mid-1980s. In both cases, the estimated breakpoints precede the onset of shifts in labor productivity growth, as they have come to be conventionally recognized.[3]

A number of explanations for a delayed impact of technological innovation on productivity have been proposed in the literature. For example, some models incorporate lags associated with the adaptation and diffusion of technical knowledge (e.g. Hornstein and Krusell, 1996; Jovanovic and MacDonald, 1994; Greenwood and Yorukoglu, 1997; Andolfatto and MacDonald, 1998; Yorukoglu, 1998; and Hornstein, 1999). Others

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[1]For example, Gordon (2000), Roberts (2001), and Jorgenson, Ho and Stiroh (2002) examine the transitory and permanent components of productivity growth, with differing conclusions about their relative contributions. However, these and other studies date the apparent change in productivity growth at 1995 or 1996. Hansen (2001) finds a 1994 break in productivity growth.

[2]Solow (1987).

[3]The dating of the productivity growth slowdown in 1973 has become the received wisdom, from at least as far back as Dennison (1985).

consider human capital accumulation as a specific source of the lag (e.g. Collard, 1999; Perli and Sakellaris, 1998; and Ozlu, 1996).  Basu, Fernald and Shapiro (2001) propose several sources of friction associated with adjustment costs and factor utilization rates. Models of "general purpose technologies," as described in Helpman (1998), and other R&D and Schumpeterian growth models like those of Aghion and Howitt (1992) also suggest delays in the productivity-enhancing effects of technological innovations. Historical analyses such as those of  David (1990) and Mazzucato (2002) have been cited as evidence of some of these effects.

In this paper,  I examine a more fundamental explanation involving the capital-deepening component of the standard neoclassical growth paradigm. Using dynamic simulations of a model that accommodates stochastic trends in technological growth rates, I demonstrate how shifts in technology growth engender capital-stock  transition dynamics that tend to delay the response of productivity growth in a way that is generally consistent with patterns seen in the data.[4]

In particular, the model simulations are consistent with the evidence that the slowdown in neutral technology growth in the late 1960s was followed by a period of increased capital accumulation, delaying the evident onset of the productivity growth slowdown until the early 1970s; and that the acceleration of investment-specific technological progress in the 1980s was followed by a period of slow capital growth, suppressing labor productivity growth until the 1990s.  The ability of this basic model to generally match these features of  the data suggests this endogenous capital-deepening channel as a potentially important factor in accounting for productivity growth patterns, in conjunction with the adaptation and diffusion lags that have been proposed in the literature.

## 1.  A Simple Illustration

Before turning to an analysis of the data and the full articulation of the model, a simple example can be used to illustrate growth-accounting implications of the capital transition dynamics considered in this paper.  Consider a simple Cobb-Douglas production function with fixed labor supply and labor augmenting technical progress:

$$Y_t = K_t^{\alpha}(X_t \overline{N})^{1-\alpha}$$

Along a steady state growth path, standard restrictions require the growth of output and capital will be equal to the exogenous growth rate of technology: $\gamma_Y = \gamma_K = \gamma_X$, where $\gamma$ is

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[4]In a previous paper on the subject of technology growth and transition dynamics (Pakko, 2002b), I examined a model that is subject to transitory shocks to both the level of technology and to the growth rate of technology—showing that the latter contribute significantly to the overall ability of the model to explain the pattern of observed economic fluctuations.

used to denote (gross) growth rates. In the absence of investment-specific technology growth, consumption and investment grow at this common trend rate as well.

As a growth-accounting exercise, it is common to decompose labor productivity growth into components measuring TFP growth and capital-deepening:

$$\Delta \ln\left(\frac{Y_t}{N}\right) = \Delta \ln(Z_t) + \alpha \cdot \Delta \ln\left(\frac{K_t}{N}\right) \tag{1}$$

where TFP growth, $\Delta\ln(Z_t)= (1-\alpha)\Delta\ln(X_t)$, is calculated as a residual. These two components are often treated as being orthogonal, with the capital-deepening component considered as a largely exogenous (or irrelevant) factor.

Now suppose that the steady-state growth rate of technological progress were to increase from $\gamma_X$ to $\gamma_X'$. The implied path of potential labor productivity growth and its capital deepening component are illustrated by the solid lines in Figure 1.

In a setting where risk-averse households control the technology, making intertemporal optimization decisions, the increase in the growth rate of technological progress will be associated with an increase in equilibrium real rates of return: Using a standard isoelastic preference-specification, the long-run real interest rate depends on the consumption growth rate, the coefficient of relative risk aversion, and the household discount factor, as given by the steady-state Euler equation: $R = \gamma_c^\sigma/\beta$.

At the higher rate of return implied by the increase in technology growth, the optimal marginal product of capital rises, requiring the capital/labor ratio to fall. But the consumption-smoothing behavior of households implies that capital growth will adjust only incrementally to this new steady state path. Moreover, a wealth effect associated with the realization of a higher steady-state growth rate engenders an immediate increase in consumption, suppressing investment and capital accumulation so that capital growth initially falls below its initial steady-state rate.[5] Along the transition path, shown by the dashed lines in Figure 1, the capital-deepening component suppresses overall labor productivity growth, so that it adjusts to its new steady-state growth path only gradually over time.

[Figure 1]

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[5]As the coefficient of relative risk aversion approaches zero, the initial decline in capital growth becomes smaller and the transition to the new steady-state growth path takes place more quickly. In the limit, with risk-neutral households, actual growth paths follow the technological potential rates precisely. The transition paths in Figure 1 are generated by a model simulation using logarithmic preferences ($\sigma =1$).

## 2. Neutral and Investment-Specific Technology Growth

The increase in productivity growth observed in the mid-1990s is commonly attributed to advances in information-technology (IT). Consequently, research on the topic has been particularly focused measuring the role of technological progress in these sectors.[6] An important feature of IT advances is that their effects are widely viewed as being embodied in the capital stock. Higher productivity arises from these advances not simply because factors are utilized more efficiently, but because new forms of higher-quality capital have become available.

### 2.1 Theoretical Framework

One framework that represents this notion of embodiment is the investment-specific technology model proposed by Greenwood, Hercowitz and Krusell (1997,2000). The model includes the standard TFP form of technology:

$$Y_t = Z_t K_t^\alpha N_t^{1-\alpha} \tag{2}$$

where growth in $Z_t$, is associated with balanced, or Hicks-neutral technological progress.[7]

Investment specific technological progress is represented in the capital accumulation equation:

$$K_{t+1} = (1 - \delta)K_t + Q_t I_t \tag{3}$$

Growth in the investment-specific technology index, $Q_t$, is associated with progress that is manifested through the accumulation of more efficient or higher quality capital goods.[8] Output and productivity growth are affected indirectly as increases in $Q$ raise the effective capital stock that enters into the production function.[9]

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[6]See, for example, Oliner and Sichel (1994, 2000, 2002); Jorgenson and Stiroh (1999); Jorgenson (2001); Stiroh (2002); and Jorgenson, Ho and Stiroh (2000,2002).

[7]As long as the production function is modeled as Cobb-Douglas, the specification in (2) is equivalent to the labor-augmenting form of technological progress discussed earlier: $Y_t = F[K_t,(X_t N_t)]$.

[8]Hercowitz (1998) relates this representation of investment-specific technological change to the "embodiment controversy"of Solow (1960) and Jorgenson (1966).

[9]For a more general discussion of the distinctions between these two sources of productivity growth, see Pakko (2002a).

The long-run growth rates of output and productivity depend on both technology variables, $Z_t$ and $Q_t$. In conjunction with a budget constraint, we can derive the usual steady-state restrictions that output, consumption and investment per capita will grow at a common rate: $\gamma_Y = \gamma_C = \gamma_I$. However, in the presence of investment-specific technological change the growth rate of the capital stock also reflects improvements in the productive efficiency of capital goods:

$$\gamma_K = \gamma_I \gamma_Q. \tag{4}$$

Working through the capital deepening channel, investment specific technology growth provides an independent source of growth for output and productivity. Specifically, the production technology determines the relationship between output growth and the underlying technology growth rates as:

$$\gamma_Y = \gamma_Z^{\frac{1}{1-\alpha}} \gamma_Q^{\frac{\alpha}{1-\alpha}}. \tag{5}$$

A shift in either the neutral or investment-specific technology growth rates gives rise to a change in the potential growth rate of output and productivity.


## 2.2 Measuring Investment Specific Technology

As emphasized by Greenwood, Hercowitz and Krusell (1997), growth accounting in the presence of investment-specific technological progress requires some modification of the data from the national income and product accounts.

The model is denominated in consumption-units, with $Q_t$ representing the relative price of effective investment. Proper accounting for neutral and investment specific technology requires that the data reflect the same structure. Hence, real output and investment should be deflated from nominal quantities by using a consumption price index. Following the practice of previous analyses, the measure of consumption used here consists of nondurables plus services (less housing services).[10] Output is represented by nominal gross domestic business product divided by the consumption price deflator. Output per hour is then calculated as the ratio of this measure of production to total business sector hours from the BLS productivity accounts.

The measurement of quality change in the national accounts is an important consideration for constructing empirical counterparts to the model's variables. In order to provide an accounting that is complete as possible, previous studies have used Gordon's (1990) estimates of quality-change that is not reflected in the official data.

The bottom line of Gordon's study was that the official NIPA data (as constructed at the time) understated the true growth rate of spending for producers' durable equipment by nearly 3 percentage points per year over his post-war sample period.

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[10]Components are aggregated using chain-weighting.

Because Gordon's data set extends only through 1983, previous estimates of investment-specific technology growth have been based on extrapolation of Gordon's aggregate data.[11]

But as BEA definitions and methodologies are updated and as relative shares of the components of equipment investment change over time, simple extrapolation of Gordon's aggregate data becomes less satisfactory. Ideally, one would like to have extended data series at the disaggregated level of Gordon's original study. A less ambitious alternative is to extrapolate the drift ratios for each of Gordon's 22 major investment categories independently—accounting for changes in BEA definitions and methodology—then aggregate the extrapolated data to calculate a new, extended series.

Such a procedure is implemented here, using estimates based on a linear extrapolation of Gordon's drift ratios for the period 1973-83.[12] The extrapolated drift ratios were applied to the more recent NIPA price data to create extended quality-adjusted series for the individual categories of investment goods. The data for individual categories were then chain-weighted to yield an aggregate quality-adjusted measure of fixed investment in equipment and software.

Special attention was paid to changes in BEA definitions and methodology. In particular, adjustments were made to account for methodological changes that have improved the measurement of quality change, obviating the use of Gordon's adjustment factors. One important innovation made in 1996 was the inclusion of software as an investment component. Gordon's data set did not include software, so the official BEA measure for this component is used, assuming that quality-change is properly measured. Similarly, the BEA has devoted considerable effort to accurately measuring quality change for computers and peripheral equipment; hence, we assume that the bias found by Gordon in the vintage data has been eliminated in contemporary time series estimates for that component. Extrapolations of the data for communications equipment and autos were also treated with special attention to take account of updated procedures adopted by the BEA for measuring quality change in those categories. These and other details of the data construction are documented in a Data Appendix.[13]

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[11]For example, Greenwood, Hercowitz, and Krusell extended the Gordon data through 1990 by adding 1.5 percent to the growth rates of real investment spending for all categories except computers. Hornstein (1999) invoked a similar procedure to extend the estimate through 1997.

[12]Data are extrapolated using only the last ten years of the sample period in recognition Gordon's observation that the magnitude unmeasured quality change was generally much smaller in the latter part of his sample period, "consistent with the straightforward hypothesis that the PPI does a better job of correcting for quality change now than was true thirty-five or forty years ago." (Gordon, 1990, p. 538).

[13]The data set was compiled prior to the BEA's December 2003 revision of the data for fixed-assets.

In addition to equipment and software, another important component of the capital stock is nonresidential structures—accounting for approximately 35 percent of nominal nonresidential fixed investment in the period 1948-2001.  Gort, Greenwood, and Rupert (1999) examined the measurement of quality improvement in structures, and estimated that the official NIPA investment data understate real, quality-adjusted growth by approximately 1 percent per year.

To account for this source of investment-specific technology growth, an adjusted measure of this component was constructed by adding 1 percentage point to each year's growth rate in real nonresidential investment (subtracting 1 percent growth annually from the growth rate of its price index).  The resulting adjusted series is then aggregated by chain-weighting with the adjusted measure of equipment and software investment, to produce a quality-adjusted aggregate for total private nonresidential fixed investment.

## 1.3  Growth Accounting with Investment-Specific Technology

The data for quality-adjusted investment and its associated price index form the basis for estimating the contribution of investment-specific technology to productivity growth.   First an index of investment-specific technology, $Q$, is constructed as the ratio of the consumption price index to the price index for (quality-adjusted) investment goods.

The estimates of $Q$, along with associated data for quality-adjusted investment are then used to construct an adjusted capital stock series that takes account of  investment-specific technological progress.  First, the NIPA data for investment and capital are used to back out a series of implied depreciation factors, $(1-\delta_t)$.[14]  These factors are then used to construct a capital-stock series using a perpetual-inventory method—that is, by reconstructing the capital stock using the capital accumulation equation (3) using the quality-adjusted investment data.  The initial value for the capital stock is adjusted using growth rate and level relationships implicit in the accumulation equation to relate investment/capital ratios in the adjusted and unadjusted BEA data.[15]  The growth rate of

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[14] The BEA constructs measures of net stocks for individual components, then uses chain-weighted aggregation to build aggregates.  The use of annual depreciation factors provides an approximate adjustment for changes in the composition of the capital stock and total depreciation that arise from this procedure.

[15] In particular, the accumulation equation implies the steady-state relationship $QI/K =[\gamma_K - (1-\delta)]$. Using a prime mark (') to indicate values from the unadjusted BEA data, the adjusted capital stock is initialized from the relationship $K/K' =QI [\gamma_K' - (1-\delta)]/Q' I' [\gamma_K - (1-\delta)]$, where initial values were used for investment data, and the $\gamma_K$ values were calculated using averages for the first ten years of output and Q-growth. This calculation, which relies on an assumption that the sample period began with the economy on (or close to) its steady-state growth path, yields initial values for the adjusted capital series of about one-third the level of the BEA data.

the adjusted capital stock exceeds its unadjusted BEA counterpart by about 2.3 percent over the period 1950-2001, but the pattern of fluctuations in capital growth is affected little by the incorporation of unmeasured quality improvement: the official and adjusted measures move closely together, having a correlation of 0.88. Regardless of the measure used, capital growth reached a peak in the late 1960s and slowed dramatically in the late-1980s.

With the capital stock adjusted to incorporate growth associated with investment-specific technological progress, the final step in the growth accounting procedure is to calculate the remaining technology that takes the form of total factor productivity, using the growth accounting relationship in equation (1).[16]

Figure 2 shows the measures of technology derived from this procedure. As found in previous studies, the explicit inclusion of investment-specific technology growth has the effect of lowering measured TFP growth. Since the early 1970s, growth in $Z_t$ has been negligible on average, with potential productivity growth driven almost entirely by $Q_t$. Cursory inspection of the trends for the two types of technological progress also suggests the possibility that shifts in growth rates preceded changes in productivity growth in the early 1970s and mid-1990s: There is a clear slowdown in neutral technology growth in the late 1960s, and the appearance of an acceleration of investment-specific technology growth sometime in the mid-1980s.

[FIGURE 2]


## 3. Identifying Shifts in Technology Growth Trends

### 3.1 Tests for Structural Breaks

Formal time-series tests for structural breaks confirm the presence of these trend shifts. Modeling each of the technology growth series an AR(1) process with a constant term, the tests reported in Table 1 present evidence of statistically significant breaks in each of the technology series.[17]

For neutral technology growth, Bai's (1994) least-squares variance test identifies a clear breakpoint in 1967. Tests of structural change based on Chow sequences identify the same date being associated with a shift in the constant term, as well as a shift in the

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[16]For both the growth-accounting exercise and the parameterized model simulations presented below, capital's share ($\alpha$) is set to 0.30.

[17] Hansen's (2001) survey paper on techniques for identifying structural breakpoints includes a description of each of the tests reported here.

full regression (a joint test for a break in the constant term and the autoregressive coefficient). In both cases, supremum test statistics exceed Andrews (1993) critical values for significance at the 5 percent level.

For investment-specific technology growth the specific timing of a structural shift is not as clear, but its presence is nevertheless confirmed. The least-squares variance test identifies 1983 as the breakdate, as does the Andrews test for a structural change in the full regression.[18] Testing specifically for a change in the constant term, there is a local maximum in the Chow sequence in 1983 that exceeds a 10 percent Andrews test statistic, but it is dominated in the supremum test by a peak in 1987. The indication of a 1987 breakdate for the mean is significant at the 10 percent level, with an approximate p-value of 0.06 (calculated using the method of Hansen, 1997).[19]

Coefficient estimates from the regressions associated with these break dates indicate that the mean growth rate of neutral technology declined from 1.71 percent to 0.13 percent in 1967, and that the growth rate of investment-specific technology rose from 2.22 percent to 3.70 percent in 1987. In terms of technologically feasible labor-productivity growth, equation (5) relates these estimates to an initial decline of 2.3 percent, and a subsequent increase of 0.6 percent.

As a test of the robustness of these findings, Table 1 also reports break-point tests for two alternative sets of technology growth rates. The first set uses the unadjusted BEA data, the second uses the extrapolated values of Gordon's drift-ratios for equipment investment as estimated by Cummins and Violante (2002).[20] The Cummins-Violante factors were used to construct technology growth variables using an identical procedure to that described in the previous section.

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[18]Tests for structural breaks in an alternative measure of $Q$ constructed using NIPA data–without adjustment for unmeasured quality-change–yield similar results, verifying that the estimated breakdate is

[19]Tests for a change in the autoregressive parameter alone (not reported in Table 1) suggest a possible break in 1989, but it is not statistically significant (p-value = 0.12).

[20]Cummins and Violante use a procedure similar the one used here, but they used time-series forecasting methods rather than simple linear extrapolation to extend the series. They did not, however, explicitly adjust for some of the methodological improvements adopted by the BEA that are considered here. On average, the growth rate of investment-specific technology calculated using the Cummins and Violante data exceeds my measure by more than one percentage point over the period 1984-2001.

**TESTS FOR STRUCTURAL BREAKS IN TECHNOLOGY GROWTH** [a]

| | Least-Squares Variance Test [b] | Chow Tests for Structural Breaks | | | | | |
| | | Full Regression | | | Constant Term | | |
| **Variable** | Breakdate [90% C.I.] | Breakdate | Sup(W) | P-value [c] | Breakdate | Sup(W) | P-value [c] |
|---|---|---|---|---|---|---|---|
| $Z$ | 1967 | 1967 | 12.808** | .024 | 1967 | 8.454** | .045 |
| $Z_{BEA}$ | 1967 | 1967 | 17.664** | .003 | 1967 | 12.442** | .007 |
| $Z_{CV}$ | 1967 | 1967 | 14.873** | .010 | 1967 | 10.038** | .021 |
| $Q$ | 1983 | 1983 | 11.289** | .047 | 1987 | 7.785* | .061 |
| $Q_{BEA}$ | 1983 | 1983 | 20.831** | .007 | 1987 | 16.413** | .001 |
| $Q_{CV}$ | 1983 | 1983 | 31.316** | .000 | 1983 | 13.691** | .004 |

* (**) Exceeds the 90% (95%) critical values using a 20% trim, as calculated by Andrews (1993)

[a] AR(1) specification of logged first differences; sample period 1951-2001.

[b] Breakdate and confidence interval estimation using the method of Bai (1994).

[c] Approximate asymptotic p-values as calculated by Hansen (1997)

All three measures of neutral technology growth identify the 1967 breakpoint. Similarly, the least-squares variance tests and the Chow tests for a break in the full regression suggest a shift in investment specific technology growth in 1983. Although tests of the series based on the Cummins-Violante data suggest a break in the constant term in 1983 as well, the series using unadjusted BEA data confirms the 1987 breakpoint (at a higher significance level). That the unadjusted BEA data suggest the same breakpoints as the adjusted data is reassuring—suggesting that the findings are not unduly biased by the extrapolation procedures used to update the Gordon data set.

As will be shown below, estimates from a Markov switching model also support the 1987 breakdate.

## 3.2 A Regime-Shifting Model

As an alternative approach to identifying shifts in technology growth rates, a two-state Markov-switching model (Hamilton, 1990, 1994) was fitted to each of the technology growth series.[21]  For $x_t = \Delta\ln(Z_t)$, $\Delta\ln(Q_t)$,

$$[x_t - \mu_x(s_{xt})] = r_x[x_{t-1} - \mu(s_{xt-1})] + \sigma(s_{xt})\varepsilon_{xt} \tag{6}$$

where the means, $\mu$, and standard deviations, $\sigma$, are functions of the unobservable two-state index variable, $s_{xt}$, and $\varepsilon_{xt} \sim N(0,1)$.  The indicator variables follow Markov chains:

$$prob(s_{xt} = j | s_{xt-1} = i) = p_{ij}, \quad i,j = 1,2. \tag{7}$$

In the estimation, state 1 is taken to be the initial state—the high-growth state for $Z$ and the lower-growth state for $Q$.

Hamilton's (1994) method for estimating this type of model employs a Bayesian state-space filtering algorithm for generating conditional estimates of the state at each point in time.  In particular, inferences about the state variable are estimated by iterating on equations (8) and (9):

$$\xi_{t|t} = \frac{\xi_{t|t-1} \otimes \eta_t}{\xi'_{t|t-1}\eta_t} \tag{8}$$

$$\xi_{t+1|t} = P\xi_{t|t} \tag{9}$$

where the $\xi$ are two-element vectors representing estimated probabilities of being in states 1 or 2, $P$ is the Markov-transition matrix with elements given by (7), $\eta_t$ is a vector of the conditional densities, $f(x \mid s_{xt})$, and the symbol $\otimes$ denotes element-by-element multiplication.

By assuming that the conditional densities are represented by mixed normal distributions, equations (8) and (9) can be used to estimate the parameters of the model values using maximum-likelihood techniques. The parameter estimates found using this approach are reported in Table 2.  For both technology growth variables, the high-growth and low-growth states are quite persistent, with transition probabilities associated with staying in the current state very close to one.  Note that the mean growths rates are nearly identical to those found in the structural break-test regressions reported above.

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[21]French (2001) uses a similar approach for estimating changes in the trend of total factor productivity growth.

**PARAMETER ESTIMATES FOR MARKOV-SWITCHING MODELS***

| Variable | $\mu(1)$ | $\mu(2)$ | r | $\sigma^2(1)$ | $\sigma^2(2)$ | p(1,1) | p(2,2) |
|---|---|---|---|---|---|---|---|
| **Z** | 1.747 | 0.176 | -0.037 | 4.206 | 3.313 | 0.967 | 0.978 |
| | (0.654) | (0.362) | (0.170) | (2.049) | (0.863) | (0.048) | (0.028) |
| **Q** | 2.334 | 3.758 | 0.194 | 3.949 | 0.535 | 0.978 | 0.963 |
| | (0.412) | (0.262) | (0.136) | (0.938) | (0.232) | (0.028) | (0.054) |

* Standard errors in parentheses.

To illustrate the regime shifts identified with this estimation, note that the filtering procedure used to estimate the model generates a series of probabilistic inferences about the current state that can be used to express the conditional expectation of $x_t$ as

$$E_t(x_t) = \begin{bmatrix} \mu_1 & \mu_2 \end{bmatrix} \xi_{t|t}. \tag{10}$$

Figure 2 illustrates these estimated sequences of expected growth rates for the two technology variables, using smoothed estimates of the inferences about $\xi$. As indicated by the structural-break tests reported above, the series for neutral technology growth displays a shift that is centered on 1967. For investment specific technology growth, the estimated probability of having shifted to state 2 rises slightly in the early 1980s, but increases sharply only during the latter part of the decade, with the largest one-year change taking place in 1987.

[FIGURE 3]

## 4. Simulations in a Neoclassical Growth Model

The changes in long-run technological growth rates identified in the previous section pre-date the conventionally-recognized changes in labor productivity growth by a number of years. An important question is how we can account for the lags. As cited in the introduction, a number frictions have been proposed regarding the adaptation and diffusion of technology. In general, these explanations focus on the delays associated with the effective implementation of particular technological innovations. But in considering changes in the *growth rate* of technological progress, a more fundamental analysis of dynamics is that described in Section 1: the capital accumulation channel of the basic neoclassical growth model. In this section, I report simulations of a calibrated

DSGE model that trace out the endogenous capital-deepening effects of exogenous changes in balanced and investment-specific technological growth rates.

Two versions of the model are considered: In the first – a "full information" specification – technology growth rates are subject to one-time shifts that are unanticipated, but fully recognized once they occur. This specification corresponds to the stark nature of the structural break tests reported in Section 3.1. In the second version, agents are assumed to be solving the Markov-switching specification estimated in Section 3.2. This version of the model can be thought of as representing a "Bayesian learning" framework.

While the full information model is shown to provide a somewhat better overall fit to the data, the Bayesian learning version provides very similar long-run long run implications, verifying the robustness of the model's general implication that endogenous capital-deepening is consistent with low-frequency patterns observed in the data.

## 4.1. Model Structure

The basic structure of the model is as follows: An infinitely-lived representative household maximizes utility over consumption and leisure

$$\max E_t \sum_{j=0}^{\infty} \beta^j U(C_{t+j}, 1 - N_{t+j}),$$

subject to a budget constraint that incorporates both neutral and investment-specific technology,

$$C_t + [K_{t+1} - (1 - \delta)K_t] / Q_t = Z_t K_t^{\alpha} N_t^{1-\alpha}. \tag{11}$$

Our interest here is to consider the effects of changes in the *growth rates* of $Z_t$ and $Q_t$ on patterns of capital accumulation. The nature of these effects can be illustrated—and distinguished from those of transitory shocks to the *level* of technology—by considering the fundamental Euler equation governing capital stock dynamics:

$$\beta E_t \left\{ \frac{U_C(\cdot_{t+1}) / Q_{t+1}}{U_C(\cdot_t) / Q_t} \left[ Q_{t+1} Z_{t+1} \alpha K_{t+1}^{\alpha-1} N_{t+1}^{1-\alpha} + (1 - \delta) \right] \right\} = 1 \tag{12}$$

An increase in the expected future level of either technology variable, $Q_{t+1}$ or $Z_{t+1}$, raises the expected future marginal product of capital. An increase in $Q_t$ also raises the effective return to current investment. Shocks to the levels of the technology variables, whether transitory or permanent, have the effect of increasing investment demand, resulting in an increase in equilibrium investment and capital accumulation.

The effects of changes in the long-run growth rates of technology variables can be seen by examining a steady-state version of equation (10),

$$\left[ \alpha \left( \frac{k}{N} \right)^{\alpha-1} + (1-\delta) \right] = \frac{\gamma_C^\sigma \gamma_Q}{\beta}, \tag{13}$$

where $k = K/(\gamma_K)^t$, a stationary-inducing transformation (described more fully in the following subsection).

Equation (13) states that the equilibrium net marginal product of capital is equal to the real rate of return in the economy, which in turn depends on the underlying growth trends. (The parameter $\sigma$ represents the coefficient of relative risk aversion in consumption.)

Using the steady-state growth relationships (4) and (5), the capital/labor ratio can be expressed directly as a function of the long-run technology growth rates,

$$\left( \frac{k}{N} \right) = \left[ \frac{\gamma_Z^{\left( \frac{\sigma}{1-\alpha} \right)} \gamma_Q^{\left( \frac{1+\alpha(\sigma-1)}{1-\alpha} \right)} - \beta(1-\delta)}{\alpha\beta} \right]^{\frac{1}{\alpha-1}}. \tag{13$'$}$$

It is straightforward to show that $k/N$ is decreasing in $\gamma_Z$ and $\gamma_Q$ — a higher growth rate of technology, of either type, is associated with a lower capital/labor ratio. An increase in the growth rate of either technology variable has the direct effect of raising the growth rates of output, consumption, capital and productivity. However, the relationships shown in equations (13) and (13$'$) reveal that the increase will also be associated with a shift in the level of the capital stock (relative to labor) as the real interest rate increases and the optimal marginal product of capital rises. By lowering the equilibrium capital/labor ratio, an increase in technology growth has a transitional effect of that dampens the growth rate of capital. The effects of a shift in technology growth are therefore quite distinct from those accompanying shocks to the *level* of technology relative to trend.

## 4.2 Simulation Methodology

Simulations of the dynamic responses to these shocks are generated using standard techniques for solving a stationary log-linear approximation of the model, modified to allow for long-run technology growth rates to be subject to occasional shifts.[22]

First, a stationary representation of the model is derived by dividing each of the time-$t$ variables by growth factors, $X_{it}$, where $X_{it+1} = \gamma_X X_{it}$. As a result of this transformation, these growth factors emerge as parameters of the stationary system. For

[22]Specifically, the solution algorithms of King, Plosser and Rebelo (1988a) are adapted to allow for changes in underlying growth trend variables.

example, using lower case variables to represent transformed (stationary) variables [e.g. $k_t = K_t/X_{kt}$], the capital accumulation becomes,

$$\gamma_k k_{t+1} = (1 - \delta)k_t + q_t i_t, \tag{14}$$

and the Euler equation takes the form

$$\beta E_t \left\{ \frac{U_C(c_{t+1}, 1 - N_{t+1})/q_{t+1}}{U_C(c_t, 1 - N_{t+1})/q_t} \left( \frac{\gamma_C^{-\sigma}}{\gamma_Q} \right) \left[ \alpha q_{t+1} z_{t+1} k_{t+1}^{\alpha-1} N_{t+1}^{1-\alpha} + (1 - \delta) \right] \right\} = 1. \tag{15}$$

Equations (14) and (15) describe the important dynamics of the model economy, where changes in the lower case variables will now represent out-of-steady-state movements.[23] Equations (13) and (13′) showed that the long-run effects of changes in technology growth rates are reflected in the steady-state interest rate and the capital-labor ratio. But equation (15) differs in that it includes dynamics associated with changes in the marginal utility of consumption. Now, if we consider a shift in technology growth that changes the $\gamma$-terms in (15) the dynamic transition path will involve adjustment along margins on both the preferences-side and production-side of the model. As illustrated in section 1, risk-averse agents will seek to smooth consumption, which is associated with a gradual adjustment of the capital-labor ratio. Moreover, a wealth causes consumption growth to "jump" in the same direction as the change in technology growth, moving capital growth (and the capital-deepening component of labor-productivity growth) in the opposite direction.

To simulate these transition dynamics, I use a standard method of taking log-linear approximations of the model's equations around a baseline steady-state, then solving the resulting dynamic system using methods like those described by King, Plosser and Rebelo (1988a) and King and Watson (1998). But rather than treating the growth-trend variables as fixed parameters of the system, they are allowed to be time-varying. For example, equation (14) is linearly approximated as,

$$\left[ \frac{\gamma_k}{\gamma_k - (1 - \delta)} \right] \left( \hat{\gamma}_{kt} + \hat{k}_{t+1} \right) - \left[ \frac{(1 - \delta)}{\gamma_k - (1 - \delta)} \right] \hat{k}_t = \hat{q}_t + \hat{i}_t,$$

where the carat or "hat" values represent proportional deviations of the variables from their baseline steady-state values, and the time subscript on $\hat{\gamma}_{kt}$ represents a change in

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[23]The model also includes the standard equation that relates the marginal rate of substitution between consumption and leisure to the marginal product of labor. The specific effects of allowing for endogenous labor-leisure choice will be considered below.

the expected future growth rate relative to the baseline steady-state. Equations (4) and (5) relate the growth-rate variables in (14) and (15) to the underlying technology growth trends, which are assumed to be exogenous variables of the system.

In general, the exogenous technological growth variables take the form,

$$\hat{\gamma}_{Xt} = \rho_X \hat{\gamma}_{Xt-1} + \hat{\varepsilon}_{Xt}; \qquad X = Z, Q. \tag{16}$$

In the full-information version of the model, the autoregressive parameters, $\rho_X$, are set to unity: breaks in the technology growth rates are immediately recognized and assumed to be permanent. In the Bayesian learning version, those parameters will be determined by the mapping of the Markov-switching processes onto the AR(1) structure of the linearly approximated system.

By treating the growth trends as exogenous and time-varying, the log-linear approximation of the model is used to simulate approximate transition dynamics in response to a growth rate shifts.[24] Simulated growth rates of the underlying variables can then be recovered from simulations as the sum of the baseline steady-state growth rate, the change in the growth rate, and the first-differences of the simulated dynamic responses of model variables; for example,

$$\Delta k_t = \bar{\gamma}_k + \hat{\gamma}_{kt} + \hat{k}_t - \hat{k}_{t-1}.$$

## 4.3  A Calibrated Demonstration

The model is calibrated at an annual frequency using long-run average data, and with parameter values that are generally consistent with RBC analyses and growth accounting exercises. Capital's share of output, $\alpha$, is set to 0.30, and the capital depreciation rate, $\delta$, is calibrated to the average ratio of depreciation to the net stock of nonresidential fixed private capital in the BEA's Fixed Reproducible Tangible Wealth accounts—approximately 6.5%. The household discount factor, $\beta$, is based on a real return to capital of 6%.

For the model simulations, the form of the utility function is specified as:

$$U(C_t, 1 - N_t) = \ln(C_t) + \chi (1 - N_t)^{1-\zeta} / (1 - \zeta), \tag{17}$$

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[24]King and Rebelo (1993) employ a similar approach to simulating capital transition dynamics. Rather than considering changes in the technological growth rate, however, they evaluate perturbations of the capital stock from its long-run value to generate transition dynamics back to the steady state. The two exercises are conceptually identical, tracing the transition path of the capital stock from an initial out-of-steady-state position to its equilibrium steady-state value.

i.e., the coefficient of relative risk aversion is set to unity. The preference parameter $\chi$ is selected so that the fraction of time spent working of 0.24, and the labor supply elasticity parameter, $\zeta$, is set to equal 3.[25]

To demonstrate the dynamic adjustment paths following changes technology growth and to compare the implications of neutral and investment-specific growth shocks, consider one-time shifts that permanently raise the trend rate of productivity growth by one-half percent, from 1.5% to 2.0%. For the purposes of this demonstration, investment-specific technology growth is calibrated to account for one-half of the initial 1.5% growth trend. Changes in each of the two types of technology growth are considered independently, where each shift is calibrated to deliver the one-half percent change in productivity growth, $dln(\gamma_{Zt}) = (1-\alpha) \times .005$ or $dln(\gamma_{Qt}) = [(1-\alpha)/\alpha] \times .005$.

Figures 4 and 5 illustrate the transition dynamics associated with these shifts. The growth rate of the capital stock, shown in Figure 4, illustrates the fundamental endogenous dynamics of the long-run transition path. An increase in either type of technology growth raises the optimal marginal product of capital, giving rise to a period of slower capital growth as the capital/labor ratio adjusts to its new level. As illustrated in Figure 1, the wealth effect on consumption demand creates an initial decline in investment, so there is a period during which capital growth falls below its initial trend rate before converging to the new higher rate. The slowdown is more pronounced for a change in investment-specific technology growth, reflecting the fact that this form works directly through capital-deepening and is therefore associated with a larger eventual increase in the growth rate of the capital stock.

[FIGURE 4]

Figure 5 shows the growth rates of labor productivity and its capital-deepening component, $\alpha K/N$. These series display an additional source of dynamics that was not present in Figure 1: The initial wealth effect of the change in technology growth pertains to leisure as well as consumption, so there is decline in the growth rate of labor supply associated with the recognition of the shock. The growth shifts are modeled as changes in expected future growth from period $T$ forward, so that the potential productivity growth trend increases in periods $T+1$ and beyond. At time $T$, the wealth effect on labor

[25]The labor supply elasticity (with respect to the real wage rate) is given by $\zeta^{-1}(1-N)/N$, so that the calibrated parameter values imply that this elasticity is approximately equal to one. This value is higher than is typically found in microeconomic analysis, but lower than values commonly used to calibrate macroeconomic models. The unitary elasticity is consistent with some recent work seeking to reconcile the discrepancy between the micro and macro literature; e.g., Chang and Kim (2003, 2005). In any case, the particular value of this parameter turns out to be quantitatively unimportant in the analysis.

supply lowers work effort.  Given the predetermined capital stock, this results in a transitory increase in the growth rates of both $K_T/N_T$ and $Y_T/N_T$.  Thereafter, the transition path of the capital stock drives the adjustment dynamics of these growth rates.

[FIGURE 5]


Growth from capital deepening falls below its initial rate and only gradually converges to the new higher trend.  As a result, labor productivity growth remains below the new long-run trend for some time.  In the case of a shift in neutral technology growth, productivity growth reaches half of its ultimate increase only after 4 years.  It takes 12 years for productivity growth to reach 90 percent of its eventual increase.   The effects of transition dynamics following a shift in investment-specific growth are even more dramatic: Because it effects growth solely through the capital-deepening component, the investment-specific growth shift results in productivity growth falling *below* its original trend rate, and it takes 10 years before productivity growth reaches half of its long-run increase; 90 percent of the adjustment is achieved only after 19 years have passed.

**3.5  Model Simulations Using With Structural Breaks (Full Information)**

This section presents simulations of the full-information model using values for technology growth rates and their shifts, as estimated in the structural-break test regressions.

Figure 6 compares the model's predicted growth rates for labor productivity and the capital labor ratio to those in the data.   The model simulation identifies growth-rate paths that appear to fit the longer-run trends in the data fairly well.  The simulation produces a surge in capital deepening in the late 1960s that has the effect of delaying the slowdown in productivity growth following the downward shift in neutral technology growth.  In response to the increase in investment-specific technology growth in the late 1980s, capital deepening and overall productivity growth slow before rising gradually toward the end of the sample period.  The correspondence between the simulations and the data is clearest in the comparison of capital stock growth rates in the third panel of Figure 6.  Although the timing and magnitude of the turning points differ between actual and simulated series, both display a key peak in the late 1960s and a slowdown in the late 1980s, followed by gradual adjustment to the new steady-state growth rates.

[FIGURE 6]


As shown in the first row of Table 3, the correlations between the simulated series and the data are 0.54 for productivity and 0.24 for the capital-deepening component. Note that these correlations do not simply reflect the effects of the exogenous shifts in technology growth:  The second row of Table 3 shows the correlation of actual data with the steady-state growth components only, constructed by assuming that the relationships

in equations (4) and (5) hold period-by-period.  Without the endogenous model dynamics, the labor productivity correlation is slightly lower, but capital-deepening correlation is essentially zero.  A comparison of the slower-moving capital-stock growth rates shows this even more clearly: The correlation between actual and simulated growth rates is 0.48, while the correlation of the data with only the exogenous growth components is negative. The positive correlation for capital and the capital deepening component of labor productivity are entirely attributable to the model's endogenous dynamics.

**TABLE 3:**
**CORRELATIONS OF SIMULATED GROWTH  RATES WITH DATA**
**FULL-INFORMATION MODEL**

| Variable | Annual Growth Rates | | | Low-Pass Filtered Data* | | |
|---|---|---|---|---|---|---|
| | *Y/N* | *K/N* | *K* | *Y/N* | *K/N* | *K* |
| Correlation of Actual with Simulated Data | 0.544 | 0.243 | 0.479 | 0.973 | 0.870 | 0.606 |
| Correlation of Actual with Growth Component Only | 0.492 | 0.007 | -0.295 | 0.864 | -0.044 | -0.411 |

 * Filtered data are generated using the band-pass filter described by Christiano and Fitzgerald (2003), with a specification that isolates cyclical components with a periodicity of 12 years of longer.


Note that the higher-frequency variability in the labor productivity and capital/labor ratio, attributable to the wealth effect on labor supply, does little to contribute to the fit of the simulated variables to the data.  Hence, the inclusion of variable labor-leisure choice would not appear to contribute to the ability of the model to match longer-run productivity growth patterns.  In fact, these high frequency dynamics tend lower the correlations between actual and simulated series reported in Table 3.

To focus more directly on the slower-moving components of fluctuations, Figure 7 compares actual and simulated series that have been smoothed using the band-pass filtering method of Christiano and Fitzgerald (2003).  A low-pass filter specification was used to identify fluctuations in the data with cycle periodicity of 12 years or greater.


[FIGURE 7]

The longer-run relationship between actual and simulated series is apparent in the smoothed data, particularly for the capital growth rate and the capital-deepening component of productivity growth.. Though differing slightly in magnitude and phase, the low-frequency cycles isolated by the filter generally show striking similarities between actual and simulated series.  Correlations comparing these series, also reported in Table 3, show that the simulated and actual series are very highly correlated.  The exogenous growth shifts still account for much of the correlation between the filtered series for labor productivity, but the model's endogenous dynamics still fully account for the correspondence between actual and simulated movements in capital growth and the capital-deepening component of productivity growth.  In the absence of endogenous dynamics, the correlations in the second line are both negative.  The slight improvement in labor productivity correlations seen by comparing the two rows in Table 3 can therefore also be attributed to the endogenous dynamics of the model.

### 3.6  Model Simulations with Regime-Shifting (Learning)

Perhaps a more realistic view of changes in technology growth rates is provided by the estimates from the Markov-switching model in Section 2.3.  In this section, I consider simulations of a model in which agents are assumed to solve the inference problem given by (6)-(9), allowing for "learning" about the shift in technology growth regimes.[26]

In order to map the regime-shifting framework onto the Canonical difference-equation structure of the model, we need to express a log-linearized version of the Markov-switching process in the general form of equation (16).

It will be convenient to take the linear approximation around a baseline steady-state defined by the unconditional expectation of the two technology growth-rates, expressed as functions of the estimated parameters of the Markov-switching processes. For each of the technology growth variables, $\gamma = \gamma_z, \gamma_Q$ ;

$$\ln(\bar{\gamma}) = \frac{1 - p_{22}}{2 - p_{11} - p_{22}} \mu_1 + \frac{1 - p_{11}}{2 - p_{11} - p_{22}} \mu_2, \tag{18}$$

where the composite expressions weighting the mean growth rates are the ergodic probabilities of being in the two states.

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[26]This approach to constructing log-linear approximations of a Markov-switching process is a similar to Schorfheide (2005), in which the long-run inflation rate is modeled as being subject to regime shifts.  The analysis in this paper is a simplified application of the technique, which is supported by representation theorems in Sims (2001).

When $\gamma$ is in state 1, its logarithmic deviation from the baseline steady-state is

$$\hat{\gamma}_1 = \ln(\gamma_1) - \ln(\bar{\gamma}) = \frac{1 - p_{11}}{2 - p_{11} - p_{22}}\left(\mu_1 - \mu_2\right)$$

and when $\gamma$ is in state 2,

$$\hat{\gamma}_2 = \ln(\gamma_2) - \ln(\bar{\gamma}) = \frac{1 - p_{22}}{2 - p_{11} - p_{22}}\left(\mu_2 - \mu_1\right)$$

More generally, the conditional expectation of $\hat{\gamma}_t$ will depend on the estimated sequence of probabilities, $\xi_{t|t}$,

$$\hat{\gamma}_{Xt} = \begin{bmatrix} \hat{\gamma}_{X1} & \hat{\gamma}_{X2} \end{bmatrix} \xi_{t|t} \tag{19}$$

and from equation (9) the time-$t$ expectation of $x_{t+1}$ is

$$E_t(\hat{\gamma}_{Xt+1}) = \begin{bmatrix} \hat{\gamma}_{X1} & \hat{\gamma}_{X2} \end{bmatrix} P \xi_{t|t} \tag{20}$$

Note that the time varying nature of the growth states is entirely summarized in the vector of probability inferences, $\xi$. For the two-state Markov processes considered, it can be shown that $E_t(\hat{\gamma}_{Xt+1})/\hat{\gamma}_{Xt}$ is independent of the state, and is given by $p_{11} + p_{22} - 1$ (the stable eigenvalue of the probability transition matrix, $P$).[27] For the linearly approximated simulations, this is the appropriate value to use for $\rho_X$ in equation (16). Given the parameter values reported in Table 2, $\rho_Z = 0.945$ and $\rho_Q = 0.941$.[28] The sequence of disturbances fed into the model, which implicitly include terms associated with agents learning about the states, can then be calculated as:

$$\varepsilon_{Xt} = \hat{\gamma}_{Xt} - E_{t-1}(\hat{\gamma}_{Xt}) = \hat{\gamma}_{Xt} - \rho_X \hat{\gamma}_{Xt-1} \tag{21}$$

The trend-shift estimates derived using smoothed inferences about the state probabilities, (illustrated in Figure 2) are used to generate a simulation of this version of the model.[29] The results of this exercise, illustrated in Figure 8, show a somewhat muted

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[27]See also Hamilton (1994), p. 684.

[28]That the autoregressive terms are close to, but not equal to one reflects the property of the regime-shifting model that there is always a small probability of moving to the other state.

[29]In this case, the initial conditions of the simulation are set by running the model for 30 years prior to the start of the sample, using the initial values of $\xi_{t|t}$ (which are associated with a very high probability of being in state 1 for both technology growth rates). This initialization period

version of the simulated paths found in the full-information simulations of the model. The more gradual adjustment of expectations about changes in long-run growth rates dampens the sharp response of labor that generated high-frequency movements in *Y/N* and *K/N* in Figure 7, tending to improve the fit of the model. However, the learning framework also dampens the magnitude of capital-growth responses relative to the full-information simulations.

[FIGURE 8]

The correlations of actual and simulated data reported in Table 4 show that the learning model provides a slightly improved fit for productivity and capital-deepening relative to the full information model, but with a slightly lower correlation between actual and simulated capital stock growth rates.

**TABLE 4:**
**CORRELATIONS OF SIMULATED GROWTH  RATES WITH DATA,**
**REGIME-SHIFTING MODEL**

| Variable | Annual Growth Rates | | | Low-Pass Filtered Data* | | |
|---|---|---|---|---|---|---|
| | *Y/N* | *K/N* | *K* | *Y/N* | *K/N* | *K* |
| Correlation of Actual with Simulated Data | 0.553 | 0.369 | 0.405 | 0.967 | 0.828 | 0.476 |
| Correlation of Actual with Growth Component Only | 0.515 | 0.010 | -0.303 | 0.890 | -0.002 | -0.368 |

*Filtered data are generated using the band-pass filter described by Christiano and Fitzgerald (2003), with a specification that isolates cyclical components with a periodicity of 12 years of longer.

Again, to focus on the lower-frequency movements, Figure 9 shows actual and simulated series that have been smoothed a low-pass filter. The longer-run movements in the simulated series still correspond generally to patterns in the data, but fail to fit the magnitude of growth rate changes as well as in the full-information simulations. As was the case in the earlier simulations, however, the endogenous dynamics of the model are responsible for  the correspondence between actual and simulated growth rates of capital

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allows the capital stock to converge to near its steady-state value at the start of the sample period.

and the capital-deepening component of productivity.  In the absence of the model's dynamics, the correlation of these growth rates with the underlying technology-growth shifts are zero or negative, in both the filtered and unfiltered data comparisons.


[FIGURE 9]


## 4. CONCLUSION

The model examined in this paper suggests that the adjustment of capital to a change in technology growth implies a long period of transition before the shift is fully reflected in productivity growth.  This is particularly true if the technology change is investment-specific.

Statistical tests show that there was, in fact, an increase in the rate of investment-specific technology growth in the late 1980s, partly reversing the decline in potential growth from a downward shift in TFP growth in the late 1960s.  The pattern of capital stock growth and the capital-deepening component of productivity growth display subsequent fluctuations that are generally consistent with the model's predictions.  These findings suggest that capital adjustment dynamics have been an important factor explaining the apparent lag between the pace of technological innovation and the growth rate of labor productivity.

The adjustment mechanism identified in this paper contributes to an explanation of the lag, but is not proposed as an alternative to other theories that emphasize technology diffusion and adaptation.  For explaining the lag between early advances in ICT and their manifestation in aggregate measures of investment-specific technology growth, frictions associated with the adaptation and diffusion of technological innovations are very likely relevant.

The fact that the model does not fully predict the timing or magnitude of the trough in capital-stock growth in the early 1990s suggests that the simple framework simulated in this paper fails to account completely for the lags between the identified shift in investment-specific technology growth and the productivity acceleration of the late 1990s.

Nevertheless, the ability of the model to replicate some of the key salient features of the data suggests that the capital-adjustment channel examined here is important for evaluating patterns of productivity growth.  The analysis suggests that the rapid productivity growth of the late 1990s has its origins in accelerating technology trends dating back nearly a decade, with the lag between the technology growth shift and the productivity acceleration largely accounted for by the capital accumulation dynamics that are implicit in a neoclassical growth paradigm.

# Data Appendix

## A1. Basic Data Set: Summary

Variables are constructed as follows:

$P_I$: A quality-adjusted measure of the price deflator for private nonresidential fixed investment. Details of the quality-adjustment methodology are described below.

$P_C$: The price deflator for nondurable consumption goods and services, calculated as the ratio of nominal expenditures on nondurables plus services to a chain weighted aggregate of those two consumption components (1996 dollars).

$Q$: The relative price of quality-adjusted investment goods in terms of consumption: $P_C/P_I$

$C$: Real Consumption of nondurable goods and services, chain-weighted 1996 dollars.

$I$: Nominal private nonresidential fixed investment, deflated by $P_C$.

$Y$: Nominal gross business output, deflated by $P_C$.

$K$: The capital stock is generated iteratively from the accumulation equation, beginning with a 1948 base of equipment and structures from the Fixed Reproducible Tangible Wealth tables (BEA). Capital stock observations are updated using annual real figures for private nonresidential fixed investment and depreciation rates derived from the wealth tables (details below).

$N$: Hours of all persons, as used in the calculation of business sector productivity (BLS).

$Z$: The Solow residual, calculated using a capital share of 0.30 and a labor share of 0.70.

All variables are transformed into per capita terms using annual figures on total resident population, as reported by the U.S. Census Bureau.

## A2. Estimating and Incorporating Embodied Technological Change

In recent years, the BEA has been very diligent in adapting its methodologies to the rapid rate of innovation in the information and communications technology (ICT) sectors. In addition to the introduction of hedonic indices for computer equipment and purchased software, quality improvement has been examined and incorporated in measures for telephone switching equipment, cellular services and video players, among others. Indeed, the BEA has even changed its aggregation methodology to more

accurately measure the contribution of quality change to GDP growth: the adoption in 1996 of a chain-weighting methodology was intended to allow aggregates to track quality-improvement better over time.

Nevertheless, many economists contend that a significant amount of quality change goes unmeasured in the official statistics, particularly in cases where quality improvement is more incremental. As detailed in his 1990 book, *The Measurement of Durable Goods Prices,* Robert Gordon undertook to quantify the extent of this unmeasured quality change. Drawing data from a variety of sources, including special industry studies, *Consumer Reports*, and the Sears catalogue, Gordon compiled a data set of more than 25,000 price observations. Using a number of methodologies, he compiled the data into quality-adjusted price indexes for 105 different product categories, then aggregated the data to correspond to the individual components of the BEA's measure of producers durable equipment expenditure. In particular, he calculated a "drift ratio", representing the difference between the growth rates of his quality-adjusted price data and the official NIPA price indexes, then aggregated the components to create a new real, quality-adjusted investment series.

Table A1 shows trends in the drift ratios calculated by Gordon for individual components of investment spending. The table is organized by the more recent categories and definitions for Private Nonresidential Fixed Investment in Equipment and Software, which differs somewhat from the taxonomy used at the time of that Gordon constructed his drift ratios. (Some specific differences will be discussed in more detail below). The growth rates in Table A1 represent the spreads between the official growth rates and the growth rates of Gordon's quality-adjusted measures.

Over the span of the entire sample period, 1947-83, the drift ratios are uniformly positive, indicating unmeasured quality improvement. In many cases, the magnitude of the quality adjustments is remarkable. Not surprisingly, Gordon's estimates of unmeasured quality improvement are particularly large for the high-tech categories of computing and communications equipment (prior to the adoption by the BEA of hedonic methodologies for these categories). Drift ratios for some components of transportation equipment, particularly aircraft, also indicate substantial under-measurement of quality change over the post-war period.

Generally speaking, the magnitude of the drift ratios is smaller in the later years of the sample period (and in some cases, marginally negative). This observation is consistent with the hypothesis that the official statistics more accurately measure quality change in the 1970s and 1980s than they did in earlier decades.

The bottom-line of Gordon's study was that the official NIPA data understated the true growth rate of investment spending by nearly three percentage points over his post-war sample period. Unfortunately, because Gordon's data set extends only through 1983, some extrapolation is necessary in order to use his findings to evaluate recent U.S. economic experience.

## A3. Applying Gordon's Adjustments to Recent Data

In order to apply Gordon's quality adjustment to more recent NIPA data, it is necessary to make some assumptions about unmeasured quality adjustment in the post-1983 period. In addition, changes in the BEA's definitions and methodology implemented over the past two decades require some attention.

The basic procedure I adopt is to assume that the growth rate of unmeasured technological change over the 1983-2001 period is the same as Gordon's measured drift rate over the last 10 years of his sample. That is, Gordon's actual drift ratios are extrapolated to 2001 using the growth rates in the second column of Table A1. The drift ratios are renormalized to match the base period the NIPA data, then the price deflator for each component is divided by the corresponding drift ratio to produce a quality-adjusted measure of price for each of the components of fixed investment. Deflating the nominal series by these price indexes yield quality-adjusted measures of real investment expenditure.

The drift ratios are extrapolated on a component-by-component basis and then aggregated to create a quality-adjusted measure of total investment spending. This disaggregated approach is preferable to a simple extrapolation of the aggregate trend for two reasons: First, several changes in the BEA's definitions and methodology have, for some components, eliminated or at least mitigated the measurement problems found by Gordon. In addition, the procedure of re-aggregating the quality-adjusted components using a chain-weighting methodology allows the role of changing expenditure shares over time to be incorporated into the total investment data.

Of the changes to the BEA's definitions and methodology, most apply to the elements of information processing equipment and software. Many of these changes are consistent with recommendations from Gordon's study. First, the category previously known as "office, computing and accounting machinery" (OCAM) was divided into two categories: "computers and peripheral equipment" and "office and accounting equipment." Most of the unmeasured quality change for this component was in the computers and peripherals element, for which a hedonic price index approach was adopted in late 1985. Because current BEA practice carefully accounts for quality change, Gordon's calculations are superfluous for evaluating the growth rate of computer equipment. For the remaining elements of that category, data from Gordon's Tables 6.1 and 6.2 (which detail the construction of a deflator for OCAM) were used to separate out the computer component, with the remaining drift ratio to be applied to office and accounting machinery.

Software was incorporated as a component of fixed investment only in 1999, and was therefore not examined by Gordon. The BEA applies a hedonic approach to some components of software investment: In particular, a hedonic index is used to deflate prepackaged software, while in-house software is deflated using an input cost index.

Custom software is deflated using a weighted-average of these two deflators.[30] This practice amounts to applying a hedonic price index to about one-half of all software. For the purpose of this study, I assume that the BEA methodology accurately measures quality change in software.

Next to computers, the largest drift ratios measured by Gordon were for communications equipment. In particular, Gordon found that the official price index for telephone transmission and switching equipment (by far the largest item in the communications equipment category) vastly understated improvements associated with electronics and transmissions technologies in the 1960s and 1970s. In 1997, the BEA introduced a quality-adjusted price index for telephone switching and switchboard equipment, and carried back these revisions to 1985 in the 1999 comprehensive revision of the national accounts.[31] Because these revisions addressed the most serious concerns raised by Gordon about the measurement of quality change in communications equipment, I assume that the post-1985 data accurately reflect quality improvements. Consequently, I use Gordon's drift ratios and extrapolations only for years prior to 1985.

Another category that requires special attention is automobiles. As shown in Table 3, the automobile component showed a negative drift ratio over the 1973-83 period—suggesting that the BEA overestimated quality change over the decade. However, Gordon explains this finding as the result of a "spurious decline in the NIPA automobile deflator during 1980-83"[32] that he attributed to the use of a deflator for used cars that is inconsistent with quality-change measured in the index for new cars. (Used car sold from business enterprises to households—reflecting a reclassification from business capital to consumer durables—represent a factor that subtracts from investment.) In the absence of this inconsistency, Gordon notes that the drift ratio for automobiles would be close to zero for the 1973-83 period. In 1987, the BEA began to adjust used automobile by applying a quality-adjustment factor derived from its treatment of new car prices.[33] In the comprehensive revision of 1991, this change was carried back to years prior to 1984.[34] This change altered both the nominal and real data series on investment spending for automobiles, and largely eliminated the "spurious decline" in the

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[30] See Parker (2000) and Landefeld and Fraumeni (2001).

[31] Moulton and Seskin (1999).

[32] Gordon, p. 538.

[33] Fox (1987).

[34] Fox and Parker (1991).

automobile deflator for 1980-83.  Consequently, in extrapolating Gordon's data on quality change for autos, I assume a drift ratio equal to zero for the post 1983 period.[35]

Some other re-classifications of the components of equipment investment proved to be simple to address:  For example, the reclassification of analytical instruments from the Photocopy and Related Equipment category to the Instruments category in 1997[36] required no special adjustments, because Gordon's drift ratio applies to the combined Instruments and Photocopy Equipment category that was in use at the time.  Similarly, a reclassification of some equipment from Metalworking Machinery to Special Industry Machinery was also innocuous, since Gordon found that the deflator for the latter was based on a subset of raw prices from the former.  In calculating his drift ratios, Gordon simply applied the same factor to both categories.[37]

Finally, there is the issue of aggregation methodology.  At the time of his writing, Gordon criticized the BEA's continuing practice of using fixed-weight deflators. Particularly in light of his modifications accounting for quality change, a fixed-weight approach tends to underestimate the importance of goods that are declining in price (or increasing in quality) while overstating the importance of goods that have rising prices. Gordon proposed the use of a Törnqvist index, which uses share weights from adjacent periods to construct deflators for both the individual components of equipment purchases, and for aggregating the totals.  The BEA subsequently adopted a "Fisher ideal" chain-weighting formula that is similar to the Törnqvist approach in that it incorporates share-weights from adjacent periods that are allowed to evolve over time. While the two approaches are very similar, they are not identical.  For the purposes of this study, however, I assume that the two methodologies are essentially interchangable.   While I use Gordon's Törnqvist-aggregated measures disaggregating and re-aggregating the elements of OCAM into their contemporary definitional categories, I use the BEA's chain-weighting formula for aggregating the quality-adjusted components of investment spending.

One further modification was made to the aggregate data on equipment and software spending.  Prices in 1974 and 1975 were distorted by the removal of wage-price

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[35] In addition, because the BEA's methodological changes affected both nominal and real series, I use Gordon's actual price index figures (rather than applying his drift ratios directly to the contemporary deflator series) for years prior to 1983.

[36] This reclassification was associated with the incorporation of new data from the 1992 I-O accounts.  See Taub and Parker (1997)

[37] The "special industry machinery" component was one of six that Gordon referred to as "secondary" categories, for which the underlying price data overlapped with the other sixteen "primary" categories.

controls—a distortion that was exacerbated in Gordon's data by the use of Sears catalogue prices from the spring-summer issue, which was printed before controls were lifted (see Gordon, p. 482). The growth rates of Gordon's quality-adjusted prices therefore exhibit large fluctuations 1974 and 1975. To prevent these extreme changes from having an undue influence structural-break tests, price level data for 1974 is adjusted by linearly interpolating between price levels of 1973 and 1975. This modification leaves the average of 1974 and 1975 growth rates unchanged, but eliminates large swings evident in the original data.

## A4. Unmeasured Quality Change for Nonresidential Structures

The investment aggregate used in this paper includes both durable equipment and structures. In order to account for unmeasured quality change in the structures component of the aggregate, I use the estimate of Gort, Greenwood and Rupert (1999). That study finds that the quality-improvement in structures that is not captured in the official NIPA data amounts to approximately one percent growth per year. Consequently, I add one percentage point to each year's growth rate in real nonresidential structures over the sample period, then construct an adjusted real series. This measure is then aggregated by chain-weighting with the adjusted measure of fixed investment in equipment and software to produce a total quality-adjusted measure of private nonresidential fixed investment.

## A5. Construction of Capital Stock Data

With this measure of investment in hand, the final step in compiling a quality-adjusted data set is the construction of an aggregate capital stock measure. The procedure used to construct the capital stock measure involves modification of the BEA's estimates of fixed reproducible wealth.[38]

The BEA uses a perpetual inventory method with geometric depreciation – the same general form as in the capital accumulation equation in the model.

$$K_t = (1 - \delta)K_{t-1} + I_t \qquad \text{(A1)}$$

Each year's capital stock is constructed as he sum of undepreciated capital from the previous year plus gross investment.[39]

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[38] See Katz and Herman (1997).

[39] The net stocks calculated by the BEA are end-of-year values, with investment assumed to be placed in service, on average, at mid-year. Consequently, it is assumed in the BEA data that new

To parallel this construction, I begin be using equation (A1) with data for net stocks of private nonresidential capital and fixed investment to calculate a series of implied depreciation factors.[40]  Given a starting value for the capital stock, an adjusted measure is then constructed by applying these depreciation factors to the quality-adjusted investment series, corresponding to $Q_t I_t$ in the model.  Because the capital stock variable in the model represents capital available for production in the current year, the data are shifted by one year so that end-of-year values for the capital stock in year T are dated to represent beginning-of-period stocks in T+1.

The starting value for the capital stock is calibrated by exploiting the steady-state properties of the model.  Specifically, the accumulation equation (3) in the paper implies that the investment/capital ratio depends on the capital stock growth trend and the depreciation rate:

$$qi / k = \gamma_K - (1 - \delta). \tag{A2}$$

The ratio of the adjusted capital stock to the official BEA measure is therefore related to the implied growth rates of the two measures, as well as the initial ratio of adjusted investment to NIPA investment:

$$\frac{k^{ADJ}}{k^{NIPA}} = \frac{(qi)[\gamma_k^{ADJ} - (1 - \delta)]}{(q^{NIPA} i^{NIPA})[\gamma_k^{NIPA} - (1 - \delta)]} \tag{A3}$$

The numerator incorporates quality-adjusted investment ($qi$) and the associated growth rate of capital, $\gamma_K = \gamma_Y \gamma_Q$ while the denominator is related to official investment ($i^{NIPA}$) and a measure $\gamma_Q$ calculated official NIPA price indexes.  Taking 1948 to be the base year, the ratio of the quality-adjusted investment series to the official series is 0.44.  Average growth rates of output and the relative prices of investment to consumption over the subsequent 10-year period (1948-58) imply ratio of $k^{ADJ}$ to $k^{NIPA}$ that is approximately equal to 0.3.

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assets depreciate during their first year in service at a rate equal to one-half of the annual depreciation rate on existing assets.  This minor deviation from the capital accumulation process assumed in the model was found to make very little difference in the pattern of adjusted capital stock growth rates.  Consequently, the simpler formula which includes no depreciation for current-year investment goods was used.

[40] The BEA constructs measures of net stocks for individual components, then uses chain-weighted aggregation to build aggregates.  The use of these annual depreciation factors approximately adjusts for  changes in the composition of the capital stock and total depreciation that arise from this procedure.

Table A1:

**Drift in the Ratio of Official to Alternative Deflators for Components of
Private Nonresidential Fixed Investment in Equipment and Software**

Growth Rates (Percent)

|  | 1947-83 | 1973-83 |
|---|---|---|
| Information processing equipment and software | | |
| Computers and peripheral equipment[a] | 15.33 | 7.37 |
| Software[b] | na | na |
| Communication equipment | 6.42 | 8.13 |
| Instruments[c,d] | 3.50 | 2.99 |
| Photocopy and related equipment[c,d] | 3.50 | 2.99 |
| Office and accounting equipment[e] | 6.80 | 6.82 |
| | | |
| Industrial equipment | | |
| Fabricated metal products | 1.78 | -0.42 |
| Engines and turbines | 3.50 | 0.47 |
| Metalworking machinery | 1.15 | 0.96 |
| Special industry machinery, n.e.c.[c] | 2.47 | 2.81 |
| General industrial, incl. materials handling, equipment | 1.79 | 1.25 |
| Electrical transmiss., distrib., and industrial apparatus | 2.09 | 0.40 |
| | | |
| Transportation equipment | | |
| Trucks, buses, and truck trailers[c] | 3.00 | 0.56 |
| Autos | 1.35 | -2.07 |
| Aircraft | 8.29 | 3.65 |
| Ships and boats[c] | 1.93 | 1.39 |
| Railroad equipment | 1.47 | 1.78 |
| | | |
| Other equipment | | |
| Furniture and fixtures | 1.44 | 0.53 |
| Tractors | 1.41 | 3.17 |
| Agricultural machinery, except tractors | 0.68 | -0.19 |
| Construction machinery, except tractors | 1.62 | 0.68 |
| Mining and oilfield machinery[c] | 1.62 | 0.68 |
| Service industry machinery | 3.15 | 3.64 |
| Electrical equipment, n.e.c. | 1.08 | 0.18 |
| Other[c] | 1.98 | 1.68 |

SOURCE:  Gordon (1990), Appendix B, Appendix C and Tables 6.11 and 6.12.

NOTES:
a.   The official BEA statistics now incorporate quality-adjustment using a hedonic-price index
     approach, obviating the need to use Gordon's figures.
b.   Software expenditures have been included in official measures only since 1999.
c.   Classified by Gordon as  "secondary" category, with price data derived from primary categories.
d.   At the time of Gordon's study, Instruments and Photocopy comprised a single component.
e.   Derived from data on the category of Office, Computing and Accounting Machinery, adjusted to
     exclude computers and peripherals
n.e.c.  = not elsewhere classified.

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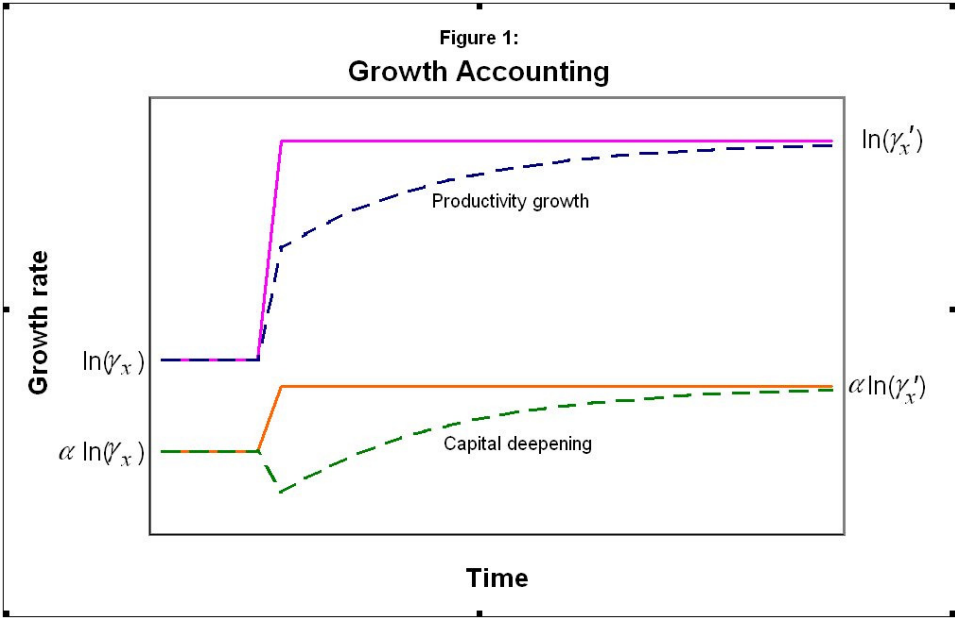
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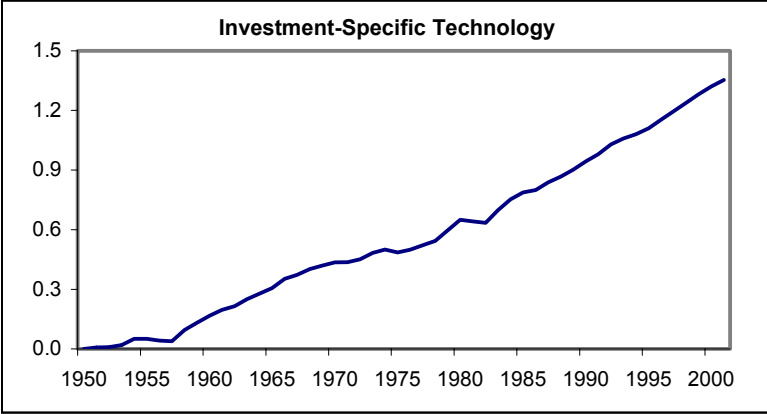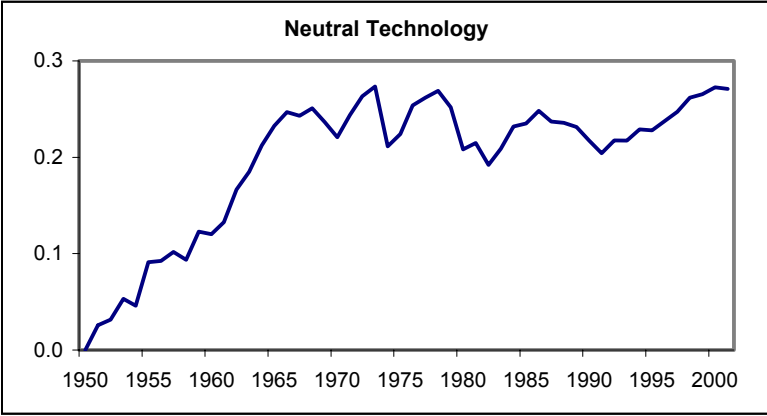
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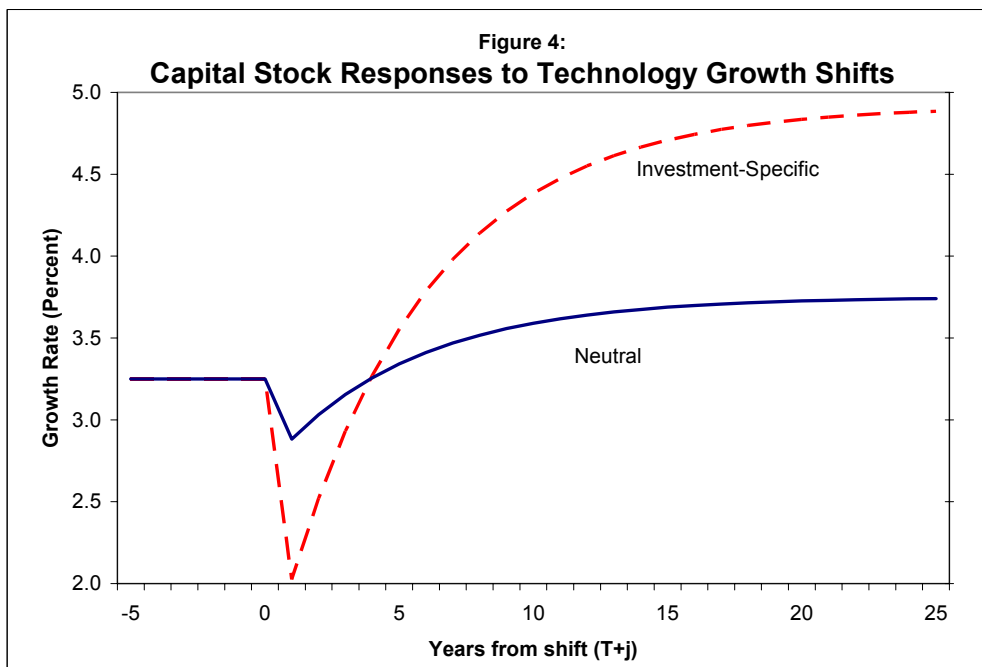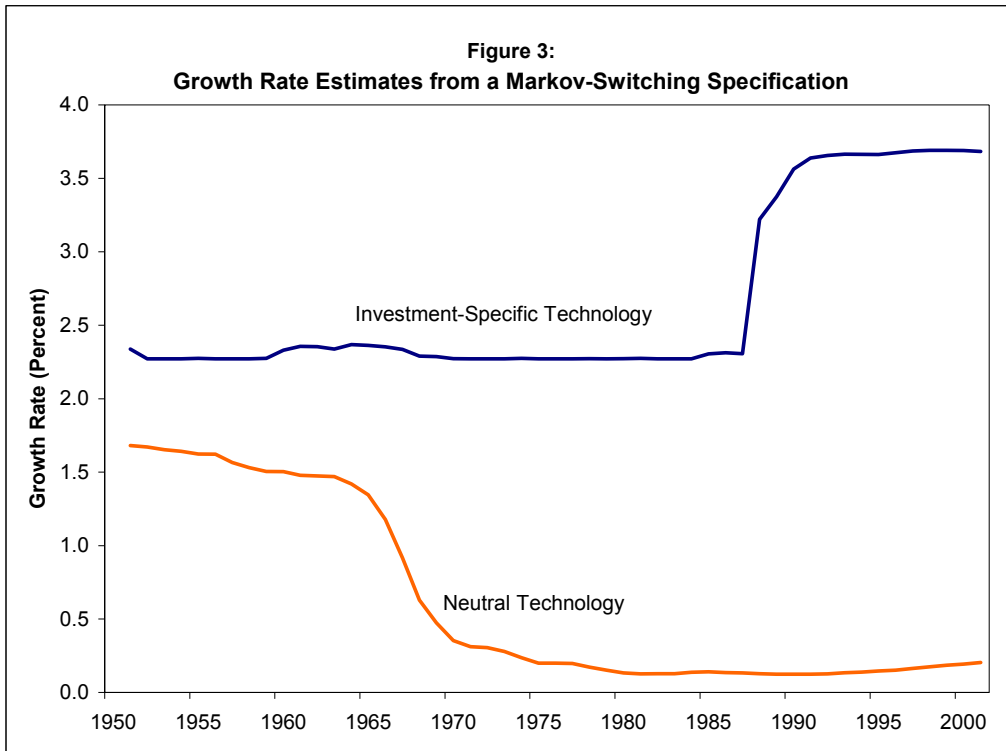
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**Figure 1:**
## Growth Accounting



Growth rate

$\ln(\gamma_x')$

Productivity growth

$\ln(\gamma_x)$

$\alpha \ln(\gamma_x')$

$\alpha \ln(\gamma_x)$

Capital deepening

**Time**

**Figure 2:**
**Neutral and Investment-Specific Technology**
(Log levels, Base = 1950)



**Neutral Technology**

**Investment-Specific Technology**

**Figure 3:**
**Growth Rate Estimates from a Markov-Switching Specification**



**Figure 4:**
**Capital Stock Responses to Technology Growth Shifts**

**Figure 5:**
## Growth Accounting Wlth Shifts In Technological Progress



**A Neutral Technology Growth Shift**

Implied Potential

Labor Productivity

Capital Deepening

Growth Rates (Percent)

Years from Shift (T+j)



**An Investment-Specific Technology Growth Shift**

Implied Potential

Labor Productivity

Capital Deepening

Growth Rates (Percent)

Years from Shift (T+j)
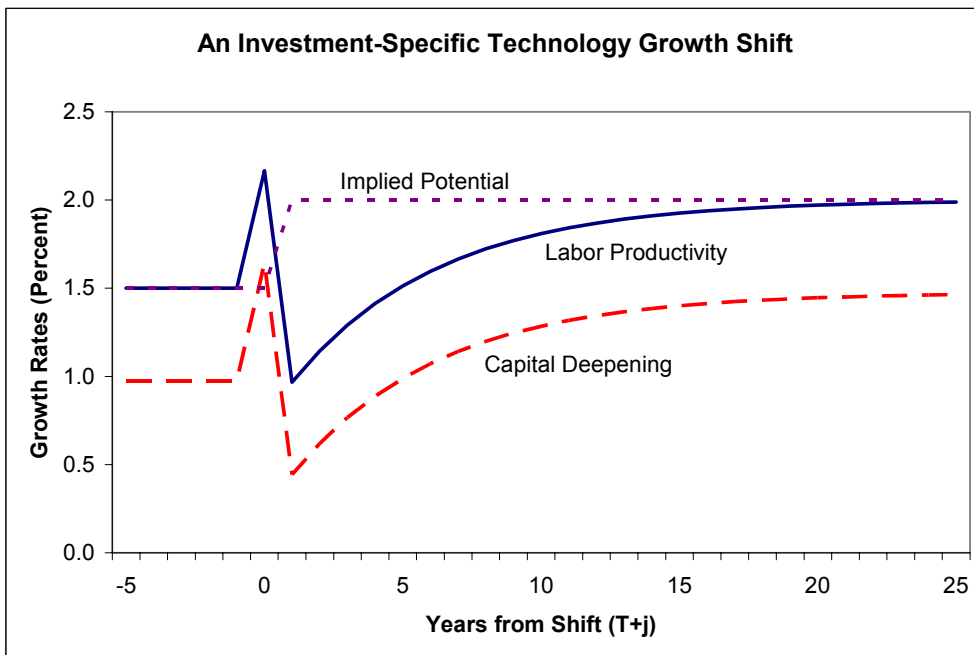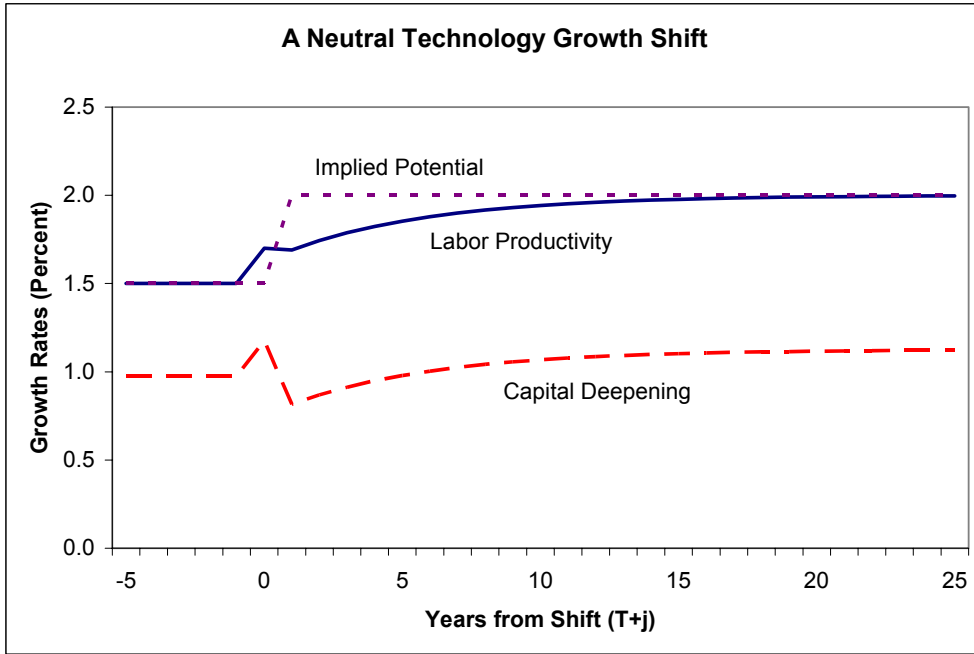
**Figure 6:**
**Actual and Simulated Growth Rates - Full Information Model**

**Labor Productivity**



**Capital Deepening Component**



**Capital Stock**



— Simulated  — · — Actual  — — Growth Component Only
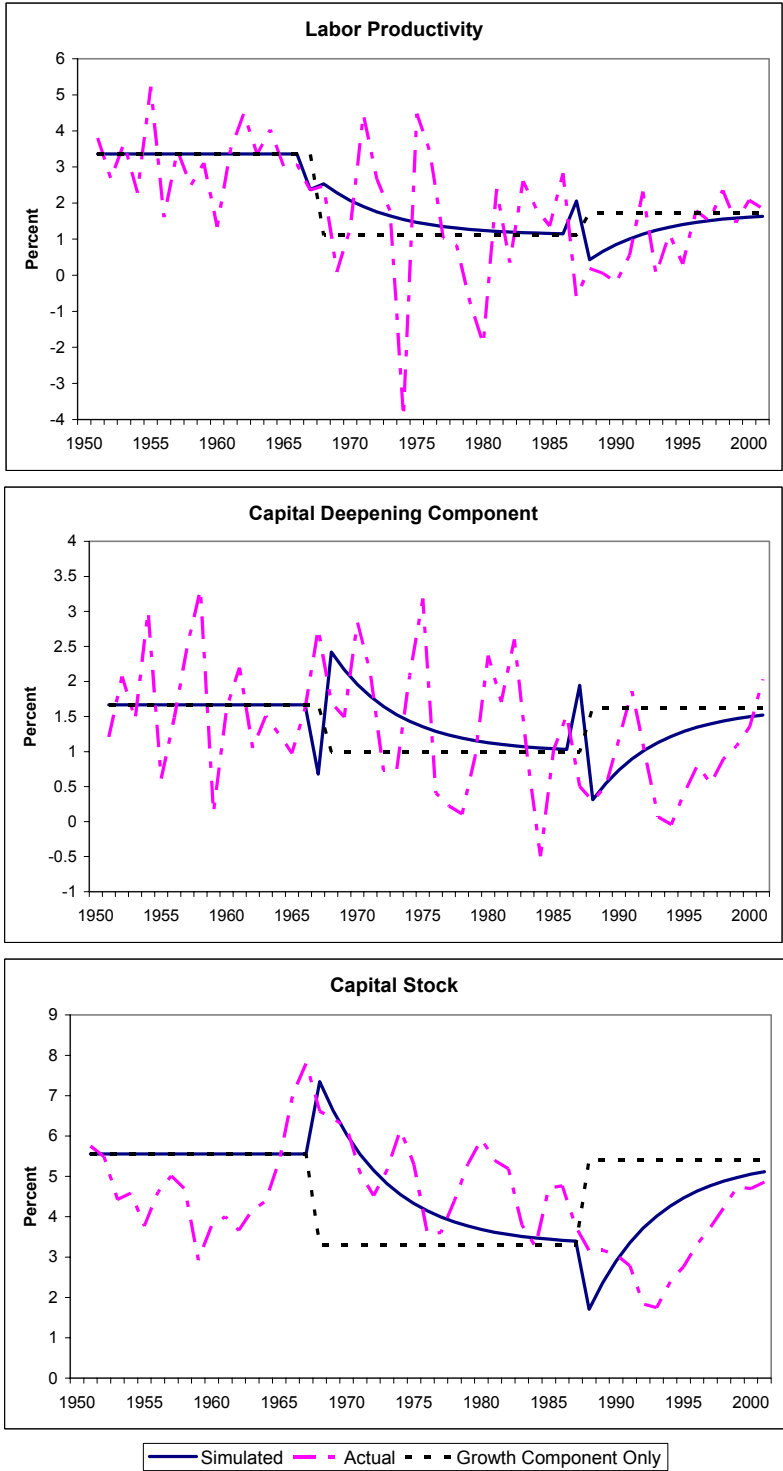
**Figure 7:**
**Actual and Simulated Growth Rates - Full Information Model**
**Low-Pass Filtered Data***

**Labor Productivity**

**Capital Deepening Component**

**Capital Stock**

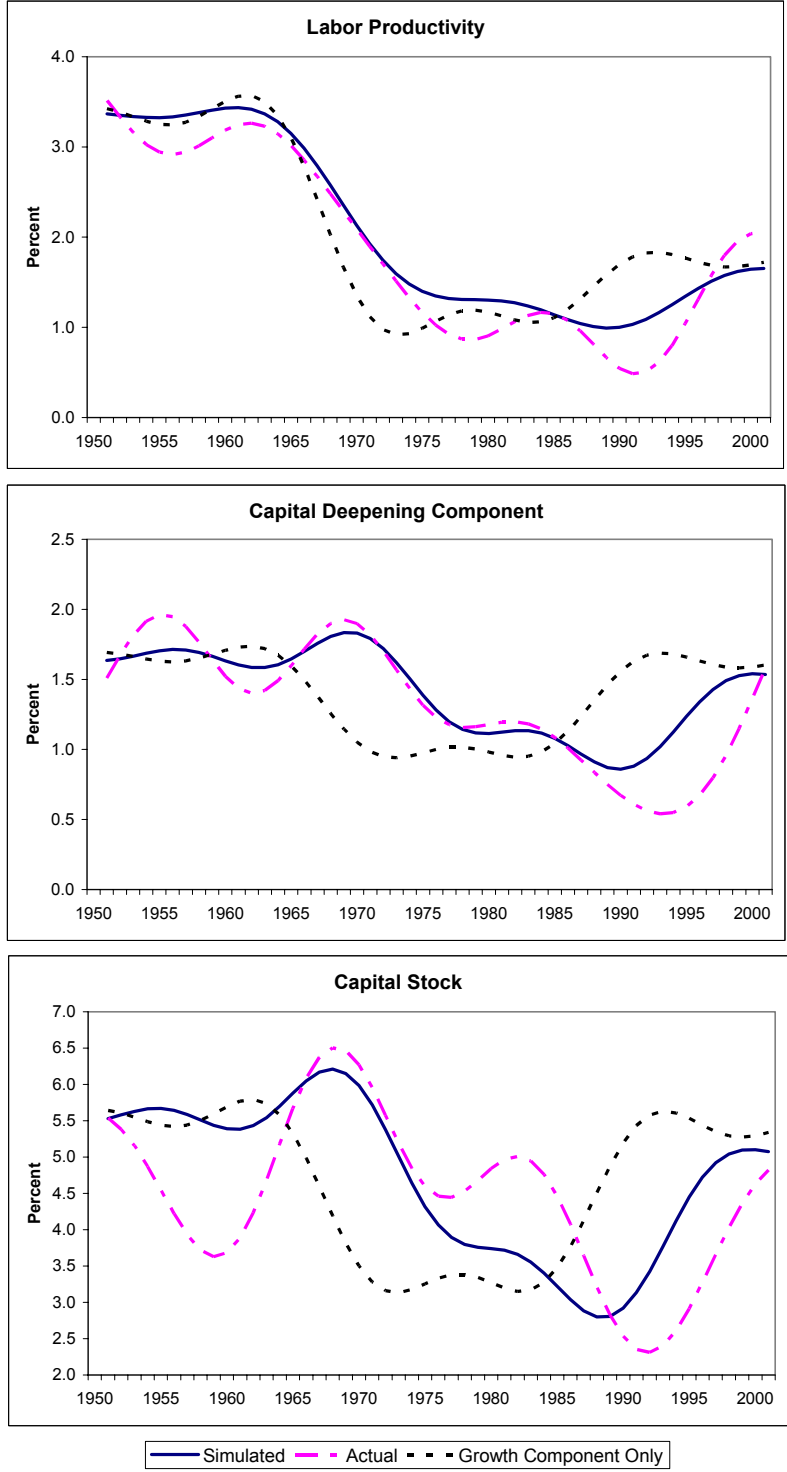Simulated — Actual — Growth Component Only

**Figure 8:**
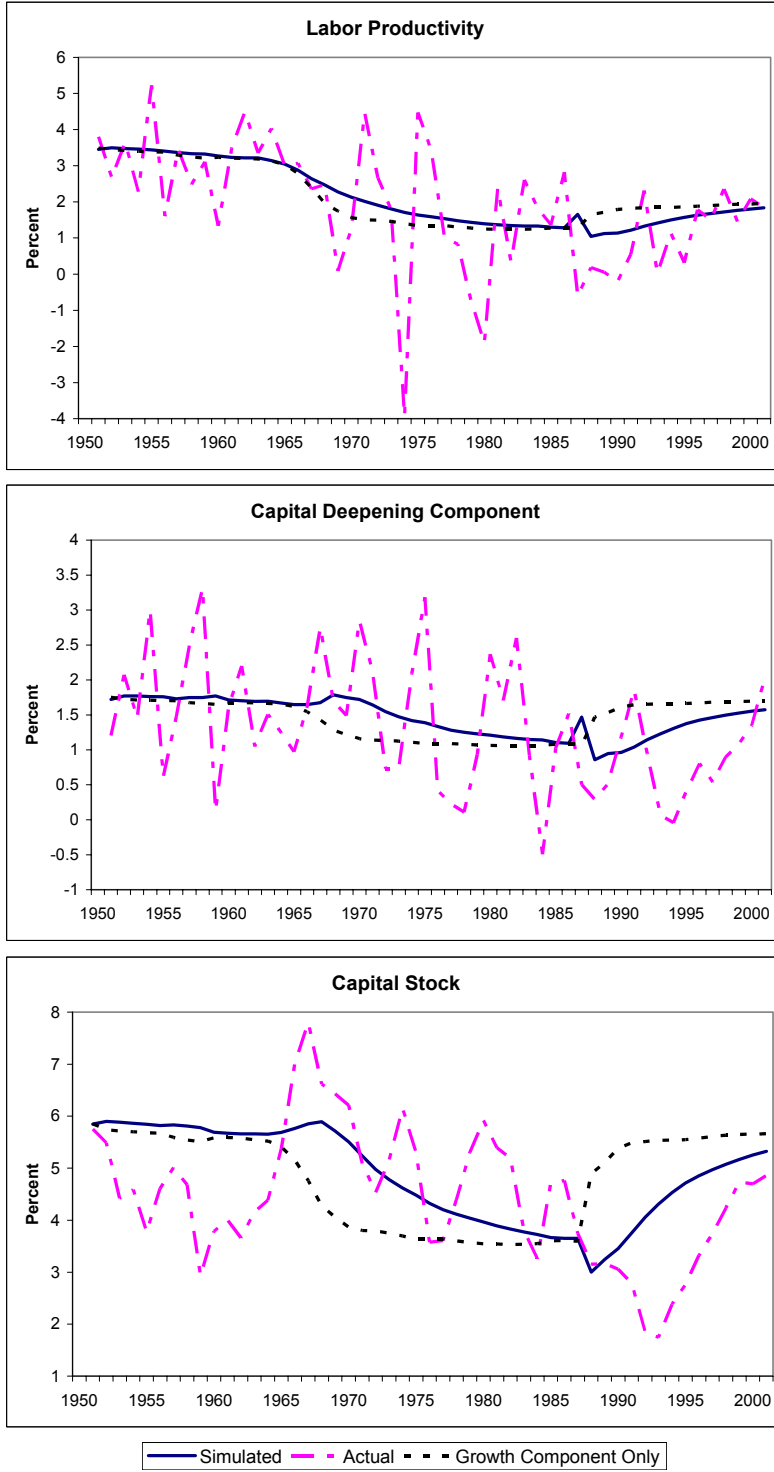**Actual and Simulated Growth Rates - Markov Switching Model**

**Figure 9:**
**Actual and Simulated Growth Rates - Markov Switching Model**
**Low-Pass Filtered Data***