What Happens When the Technology Growth Trend Changes?: Transition Dynamics, Capital Growth and the "New Economy"

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Abstract

The rapid increase in economic growth observed the late 1990s has inspired speculation about a change in the underlying trend rate of growth, attributable to an acceleration in the rate of technological progress. This paper considers the transition dynamics that are associated with such a change in the framework of a general equilibrium model that incorporates stochastic growth trends. The model suggests that endogenous transition dynamics associated with a shift in the technological growth trend can have important implications for macroeconomic growth patterns, particularly when technological change is investment-specific. Simulations of the post-WWII U.S. economy show that the model's internal propagation mechanism is capable of explaining a significant portion of the variation in growth rates over the sample period, particularly for investment, capital accumulation, and employment.

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Introduction

The increase in productivity growth during the late 1990s has raised the issue of whether a fundamental change has taken place in the U.S. economy. Although many economists remain skeptical about "new economy" or "new paradigm" theories that have emerged in this context, the conjecture that there has been a shift in the potential growth trend has been seriously entertained. Indeed, the issue is often cast in terms of whether recent trends suggest a return to growth conditions prior to the productivity growth slowdown that apparently began in the early 1970s.

In this paper, I examine the implications a change in the trend rate of technological progress in the context of a simple general equilibrium model that incorporates stochastic growth trends. The model illustrates a potentially important but often overlooked source of dynamics associated with such a change: the transition dynamics due to a change in the optimal capital/labor ratio.

Simulations of the model's responses to growth shocks suggest that long-run adjustment of the capital stock to changes in underlying growth trends gives rise to persistence in the model's dynamics, so that changes in the growth rate of technological progress may not be clearly manifested in measured productivity data for several years after the event. Moreover, the inverse relationship between the capital/labor ratio and the underlying growth trend implicit in the model's dynamics implies non-monotonic convergence paths for the growth rates of key macroeconomic variables.

Another element of many "new economy" stories that has been the subject of serious macroeconomic investigation is the notion that the productivity gains associated with recent technological advances are embedded in new forms of capital. In the spirit of this hypothesis, the model in this paper incorporates a role for capital-embodied, or investment-specific technological progress.

Simulation experiments show that the transition dynamics associated with a shift in this type of technology growth can have more dramatic implications for macroeconomic growth patterns. For a given change in productivity growth, a change in the underlying trend rate of technology growth displays both slower convergence of productivity and more variable adjustment dynamics in the growth rates of macroeconomic variables.

To examine the importance of these effect in explaining recent growth U.S. growth patterns, I take the model to the data by constructing empirical proxies for underlying technology growth trends and conducting model simulations of the post-WWII U.S. economy. The results show that the model's dynamics can explain an important share of growth fluctuations over the sample period, particularly for investment, capital accumulation, and employment. The contribution of dynamics associated with investment-specific technology growth trends is relatively modest, but has important implications for the outlook for future trends in productivity growth.

Issues and Questions

Figure 1, showing the growth of output per hour in the private business sector, is typical of the evidence used to illustrate changes in long-run growth trends. For the entire postwar sample period, the growth rate of this productivity measure averaged about 2.5%. However, the average growth rate from 1947 to 1973 was 3.3%, falling to 1.5% for the period 1973-1995. Recent data (1996-2000) suggest a growth trend has risen to 2.6%. Of course, such comparisons are quite sensitive to the sample periods selected. Nevertheless, they illustrate how the data are often parsed to demonstrate the widespread conception that there is a variable component of the underlying trend rate of productivity growth.

Focusing on the role of new information technologies in the emergence of the "new economy," recent growth accounting analyses investigating the notion of a changing growth trend have been particularly concerned with finding a role for computer-related productivity gains. For example, Gordon (1999) examines a sectoral decomposition, finding that most productivity gains in total-factor productivity are in the computer producing sector. Oliner and Sichel (1994, 2000) consider the importance of computers in the capital component of their growth accounts, finding an important role for the use of computers embedded in the growth of capital services. Jorgenson and Stiroh (1999) explicitly incorporate computer related growth in demand for investment and consumer durables. Whelan (1999b) adjusts the growth contribution of capital deepening by modeling the rapid obsolescence of computer hardware, and Kiley (1999) incorporates investment adjustment costs associated with new technologies into a growth accounting framework.

In these studies, the nature of the issue being investigated—an apparent acceleration of productivity growth in the latter half of the 1990s—necessitates analysis with limited data. As Figure 1 illustrates, however, there is a considerable amount of variation in 5-year average rates of productivity growth. Uncovering emerging trend changes is an inherently difficult endeavor.

To the extent that changes in underlying technology growth trends have predictable implications for emerging patterns of productivity growth, understanding these dynamics can be important for interpreting observed changes in growth. The model examined in this paper suggests one possible source of such patterns, which can be demonstrated using the comparative statics of a standard Solow growth model.[1]

An Illustration Using the Solow Growth Model

In the Solow growth model, output is produced using capital and labor with a constant-returns-to-scale production technology, savings is a constant fraction, s, of output, and capital depreciates at rate δ. In the presence of population growth, n and labor-augmenting technical change, g, the standard capital accumulation equation implies that capital evolves according to:

$$\Delta k = i - \delta k - nk - gk \qquad (1)$$

where k and i represent per-capita magnitudes of capital and investment (in labor efficiency units). Setting Δk=0 in equation (1) defines a locus of feasible steady-state values for the capital/labor ratio. The savings function, $s\,f(k)$ and the equilibrium condition that savings equals investment then defines a unique steady state.

Figure 2 illustrates this relationship using a familiar textbook diagram, and demonstrates the effect of an increase in the technological growth rate, from g to g'. In

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[1]See, for example, the popular macroeconomics textbook by Mankiw (1992).

the initial steady state, the capital/labor ratio is k^*. At the higher growth rate, the equilibrium real rate of return in the economy is higher, so that the optimal marginal product of capital increases. In the Figure 2, the increase in g is represented as an increase in the slope of the locus of steady states, resulting in a new long-run equilibrium that is associated with a higher marginal product of capital and hence a lower capital/labor ratio, $k^{*\prime}$.

The implication of this comparative-statics result for dynamics is that while the underlying technology growth rate – and hence the long-run growth rate of the economy – has increased, there will be a transition period in which the declining capital/labor ratio tends to suppress growth. In this simple model it is unclear how these two opposing forces might interact during the period of transition, but its basic mechanism provides the intuition for interpreting the analyses of growth shocks presented in subsequent sections of this paper.

The basic Solow growth model abstracts from household optimization over consumption-saving and labor-leisure choices, and its comparative statics fall short of providing a fully articulated description of dynamics. The model developed in the next section incorporates intertemporal optimization, endogenous labor/leisure choice, and a role for investment embodied technological progress, yet it retains much of the fundamental simplicity of the Solow growth model so as to focus on the dynamics of capital-transition paths. The first issue to be addressed is how the offsetting forces – long-run growth and capital accumulation – interact in the dynamics of a plausibly calibrated model, both for conventional neutral technological growth shocks and for investment-specific growth shocks.[2]

With these insights in hand, I take the model to the data by incorporating a limited-information setting in which agents infer the underlying growth trend by solving a signal-extraction problem. This allows for a model-consistent approach to empirically estimating the perceived trend components of data series for technology growth. Simulating the model for the post-WWII U.S. economy, I find an important role for capital transition dynamics in explaining fluctuations in the growth rates of key macroeconomic variables.

A Neoclassical Stochastic-Growth Model

Model Structure

The underlying structure of the model that I examine is quite basic: Consumers (represented by a social planner) maximize logarithmic utility over consumption and leisure,

$$\max \sum_{t=0}^{\infty} \beta^t [\ln(C_t) + \nu \ln(1 - N_t)],$$

subject to an overall resource constraint with Cobb-Douglas production:

$$Y_t = (1-\tau) Z_t K_t^{a} N_t^{1-\alpha} + \overline{T} = C_t + I_t. \qquad (2)$$

In equation 2, C_t , K_t , N_t, and I_t represent consumption, capital, labor, and gross investment, respectively. Z_t is an index of total-factor, or neutral, productivity. Income is

[2]These basic dynamics are also presented in a previous paper, Pakko (2000), where the focus is on the role of transition dynamics for conventional growth accounting exercises.

subject to a tax rate, τ, with government revenues rebated lump sum via $T=\tau Y$ (taken as given in the optimization problem).[3]

In order to incorporate the notion that the productivity-enhancing potential of recent technological progress is embodied in new capital equipment itself (particularly in for new information-processing and communications technologies), the model incorporates a role for investment-specific technological change, as modeled by Greenwood, Hercowitz and Krusell (1997,2000). Specifically, the capital accumulation equation is assumed to be:

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

where Q represents an index of the quality of new capital goods. When Q is fixed (and normalized to one), the model is a standard balanced growth model. Growth in Q is associated with technological progress that becomes embodied in the quality of the stock of capital equipment.[4]

The pair of papers by Greenwood, Hercowitz and Krusell (1997,2000), both of which focus on this type of investment-embodied technological progress, provide a convenient context for describing the distinguishing feature of the present analysis. In the first paper, Greenwood *et al* investigate the contribution of investment-embodied growth to overall economic growth in the long run. Following in the tradition of growth-accounting literature, they consider steady-state implications in terms of averages for the

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[3]Taxes are included in order to incorporate their importance for marginal decision-making (particularly their effects on the after-tax marginal product of capital and investment), and rebated lump-sum to abstract from wealth affects associated with taxation.

[4]Hercowitz (1998) relates this type of model of investment-specific technological change with the "embodiment" controversy of Solow (1960) and Jorgenson (1966) .

entire sample period covered by their data. In the second paper, which follows in the spirit of real-business-cycle analyses pioneered by Kydland and Prescott (1982), Hansen (1985) and King, Plosser and Rebelo (1988a), they examine the cyclical implications of *Q*-shocks in terms of deviations of model variables from a long run trend, where the trend is identified and removed by the application of a Hodrick-Prescott filter. The H-P filter removes slow-moving, low-frequency components of the data, implicitly allowing for a trend that is variable over time. In this paper, my focus is on that variation in longer-run underlying growth rates. That is, the model incorporates a role for stochastic growth trends.[5]

The stochastic growth aspect is modeled by assuming that each of the technology variables, *Z* and *Q*, can be decomposed into trend and cyclical components as

$$\begin{aligned} &Z_t = G_{zt} v_{zt} \quad and \quad Q_t = G_{qt} v_{qt} \\ &where \quad G_{it+1} = \gamma_{it} G_{it}, \quad i = z, q \end{aligned} \tag{4}$$

The γ_i represent growth rates of the underlying trends, while ν_{zt} and ν_{qt} are stationary cyclical components that reflect transitory shocks to technology. The latter pair of technology variables are associated with the stationary shocks commonly assumed in the real business cycle literature. The focus here is on the idea that the trend variables are also subject to stochastic variation.

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[5]Examples of similar approaches to modeling stochastic growth in a computable general equilibrium framework include King, Plosser and Rebelo (1988b); and King and Rebelo (1993).

Methodology

In this model, growth trends depend on both embodied and neutral technological change. With a stationary supply of labor (because the representative-agent aspect of the model represents per-capita quantities), standard steady-state restrictions require that output, consumption and investment will grow at a common rate γ_y. The accumulation equation (3) implies that capital will grow at a higher rate than output, as determined by the growth rate of investment specific technological progress:

$$\gamma_k = \gamma_y \gamma_q \ . \tag{5}$$

The production technology determines the relationship between output growth and the underlying technological growth rates as:

$$\gamma_y = \gamma_z^{1/(1-\alpha)} \gamma_q^{\alpha/(1-\alpha)} \tag{6}$$

A stationary representation of the model can be derived by dividing each of the time-*t* variables by growth factors, G_{it}, where $G_{it+1} = \gamma_x G_{it.}$ [each of the γ_x are related to underlying growth trends from (5) and (6)]. As a result of this transformation, long-run growth rates emerge as parameters of the stationary transformation of the problem. For example, using lower case variables to represent transformed variables [e.g. $k_t = K_t/G_{kt}$], the capital accumulation (3) becomes:

$$\gamma_k k_{t+1} = (1-\delta)k_t + q_t i_t \ . \tag{3'}$$

By treating the underlying growth rates, γ_q and γ_z, and hence γ_k, as being subject to exogenous shocks, it is possible to simulate approximate dynamics of a model in which the growth trend is stochastic.

The fundamental effect of stochastic growth trends on capital accumulation is represented in the model's Euler equation. The intertemporal efficiency condition equating the marginal product of capital to expected economic returns has a stationary representation that can be written as :

$$\beta E\left\{\left[\left(\frac{1}{\gamma_{kt+1}}\right)\frac{\lambda_{t+1}/q_{t+1}}{\lambda_t/q_t}\right]\left[q_{t+1}z_{t+1}F_k(k_{t+1},N_{t+1})+(1-\delta)\right]\right\}=1 \qquad (7)$$

where λ is the shadow value of utility (in consumption units). The first bracketed term represents the inverse of expected returns, which depends on the expected potential growth trend γ_k, and deviations in the growth rates of consumption and investment-specific technological change. The second bracketed term is the net marginal product of capital

In its steady-state form, equation (7) determines the optimal capital-labor ratio as a function of the trend growth rate of capital, γ_k. As in the Solow growth model, all else equal, a higher growth rate raises the optimal marginal product of capital — which is associated with a lower capital/labor ratio.

When the growth trend variable γ_k is subject to exogenous change, the optimal capital stock becomes variable, depending at any given time on the expected growth trend. It is the transition dynamics from one optimal capital-labor ratio to another that gives the model in this paper its unique dynamic implications.[6]

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[6]King and Rebelo (1993) examine a similar approach. Rather than considering the growth rates as stochastic directly, however, they evaluate perturbations of the capital stock from its desired long-run value, and consider the transition dynamics back to the steady state.

In the simulation experiments presented below, the model's dynamics are presented in terms of growth rates, which are constructed as follows: A log linear approximation of the model is solved and simulated using standard algorithms, producing simulated paths for model variables in terms of deviations from a baseline, constant steady-state.[7] Growth rates of key model variables are recovered from these simulations as the sum of the baseline growth trend, deviations implied by changes in the growth trends themselves, and first-differences of the model's simulated dynamics in response to the growth-trend shocks. That is, for any variable *x,* the growth rate from *t*-1 to *t* is:

$$\ln(x_t / x_{t-1}) = \bar{g}_x + g_{xt} + \hat{r}_{xt} - \hat{r}_{xt-1} \tag{8}$$

where $g_{xt} = \ln(\gamma_{xt})$ represents the deviation of the current growth trend from the baseline, $\bar{g}_x = \ln(\bar{\gamma}_x)$, and $\hat{r}_{xt}$ is the proportionate deviation of the variable from trend, as implied by the model's impulse-response functions.

Calibration

The model is calibrated at an annual frequency, with many of the parameter values chosen from previous literature to be consistent both with typical RBC analyses and growth accounting exercises. Capital's share of output, α, is set to 0.30, the preference parameter v is selected so that the fraction of time spent working of 0.24, and the discount factor, β, is approximately 0.95, based on a real return to capital of 7%. The capital depreciation rate, δ, is set to 7.5% (the average value of depreciation relative to the net stock of nonresidential fixed private capital– from the BEA's Fixed Reproducible

[7]Specifically, I use the approximation and solution techniques described by King, Plosser and Rebelo (1988a).

Tangible Wealth estimates for 1950-1999). The marginal tax rate, τ, is assumed to be 0.40.[8] Parameters describing the time series properties of the technology shocks will be defined and refined as the analysis unfolds.

Responses to Permanent Changes in Technology Growth Trends

To demonstrate the dynamic adjustment path of the model following a change in the trend rate of technological progress, a pair of stylized simulations in which the growth trend changes permanently in a once-and-for all fashion.

Specifically, I consider shifts in the underlying technology growth trends that raise the long-run rate of output and labor-productivity growth from 1.6% to 2.1%. These shifts in the underlying growth trends occur as unexpected events to agents, but are perceived to be permanent. The effects of the neutral and investment-specific shocks are normalized by using the relationships in equations (4) and (5) to back out the appropriate magnitudes for generating an increase of 0.5% in γ_y.[9]

Figure 3 shows the paths of capital and consumption (in log-levels) as they respond to a 0.5% increase in the growth rate of neutral technological change, highlighting the key features of the model's implied responses to growth shocks. The upper panel of figure 3 traces out the path of the capital stock. The higher productivity-

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[8]Greenwood, *et al* (1997,2000) include labor and capital income tax rates separately, calibrating their values at 0.40 and 0.42, respectively.

[9]For the purpose of the stylized simulations presented in this section, the baseline growth rate of investment-embodied technology growth, γ_q is set to 0.8%, so that the baseline growth rate of the capital stock is 2.4% (roughly corresponding to the growth rate of the real net stock of private nonresidential fixed assets over the period 1973 to 1995). A more detailed calibration of the model is conducted in the following section.

growth profile calls for a lower capital/labor ratio in the long run, providing a depressing effect on investment and capital accumulation immediately following the change in the growth trend.

Because this change represents a permanent level-effect, the capital stock path remains below it's original growth path for several years, and remains below the hypothetical new trend line indefinitely. On the other hand, the higher technology growth trend itself requires a higher growth rate for capital and investment in the long-run, so that over time, capital growth is in line with the new trend–simply shifted down due to the level-effect. Growth rates during the transition depend largely on which of these two effects dominate.

The lower panel of Figure 3 illustrates how consumption is affected. A wealth effect raises consumption above trend in the short run, while the downward level-shift in the capital stock is reflected gradually over time as the consumption path falls below the new hypothetical trend that would prevail in the absence of capital-stock adjustment.

In order to illustrate the growth dynamics of this exercise more clearly, Figure 4 shows the growth rates of model variables in response to positives technology-growth shifts. The solid lines show the responses to a neutral technological growth shock, while the dashed lines show the responses to an investment-embodied growth shock.

Qualitatively, the patterns of responses to the two type of technology growth shocks are similar. The wealth effect on consumption growth is apparent, and the same wealth effect is responsible for a decline in labor supply. Investment demand initially drops sharply in order to move the capital/labor ratio toward its new optimal value, then rises and converges to the new growth rate from above as capital-growth accelerates to the new higher rate implied by the shock. The initial slowdowns in employment and investment imply that output growth also slows for a time, and the gradual adjustment of the capital stock is reflected in slow convergence paths for all of the model variables.

The growth rate of labor productivity initially rises as the decline in output exceeds the decline in employment (reflecting the wealth effect on labor supply and the short-run fixity of capital). Thereafter, it drops sharply, and rises only slowly to its new long run rate as the capital accumulation process proceeds.

In the case of an investment-embodied growth shock, capital stock adjustment plays an even more pivotal role. In order for a change in the growth rate of embodied technology to generate the same acceleration in productivity growth as a neutral technological growth shift, the growth rate of the capital stock must accelerate to a higher rate in the long run (equation 6). Moreover, because the decline of the capital/labor ratio depends on the change in the growth rate of capital, the requisite level-shift of the capital stock is larger as well.

The magnified effects of an embodied technology growth shock on capital growth dynamics carry over to the behavior of other macroeconomic variables. Relative to the case of a neutral technological growth shift, the initial decline in investment demand is sharper. This puts downward pressure on the real interest rate, resulting in intertemporal substitution effects for consumption and the labor/leisure choice that reinforce the wealth effects. Because the initial negative effect on capital accumulation is larger than for the case of a neutral technology growth shock, consumption and output growth also slow sharply, then follow very protracted adjustment paths toward their new long-run trend rates of growth. The large initial decline in capital growth and investment lowers output sharply, resulting in a *decline* in productivity growth after the shift, followed by very slow adjustment to the new long-run trend. In fact, it over takes 6 years for productivity to recover to its original growth rate, and 10 years to rise half-way toward its new long run rate.[10]

Of course, some of the starkness of the dynamics that these stylized simulations deliver is attributable to the abrupt nature of the assumed shocks. When changes in the underlying trend occur more gradually, or are recognized only incrementally by the agents in the model the responses are smoother, the adjustments more moderate.[11] But the basic patterns of the responses as illustrated in Figure 4 remain.

These basic patterns predicted by the model suggest that changes in technological growth trends, by giving rise to persistent capital stock transition dynamics, can provide for a propagation mechanism that is relevant for interpreting productivity growth trends. Most relevant for the issue of assessing claims about the emergence of a "new economy" is the observation that an increase in the trend rate of technological progress, particularly one of the capital-embodied type, gives rise to a very gradual acceleration in *measured* labor productivity as capital accumulation slowly adjusts to its higher rate of growth. Therefore, we might expect that recent gains in productivity growth represent lagged responses to shifts in underlying technological trends.

[10]The rate of convergence from the low point of productivity growth toward the new trend (for both types of technology growth shocks) is associated with a half-life of about 3.7 years. The slower convergence rate in response to investment-embodied growth shocks is entirely associated with the relatively larger decline in capital stock growth.

[11]For an illustration of these characterizations, see also Pakko (2000).

The simulations also suggest a pattern to look for in the data as evidence of the relevance of this effect: changes in productivity growth are predicted to be preceded by a sharp change in the growth rate of the capital stock, in the opposite direction.

Figure 5 shows the growth patterns of one conventional measure of capital stock expressed in per capita terms[12]. The growth rate of this measure of capital exhibits a number of ups and downs over the post-WWII period. Note that the largest surge in growth occurs in the late 1960s, just prior to the time often associated with a persistent productivity slowdown. Over the next 20 years, capital growth follows a downward trend as productivity growth languished. There are a number of swings in the growth rate over this period, which are conceivably associated with revised expectations of underlying technology growth. For example, there is a second surge in capital growth that peaks in 1974, corresponding to the point at which – at least in hindsight – the productivity slowdown was clearly underway. There is a sharp decline in capital growth during 1983 and 1984, as the economy emerged from it's worst postwar recession, and another sharp decline in capital growth in the early 1990s, preceding the productivity acceleration later in the decade.[13]

Of course, such casual empiricism is far from convincing, but it at least provides *primae facie* evidence that a more rigorous investigation is warranted. The following

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[12]The capital stock measure shown in Figure 5 is the growth rate of net stocks of private nonresidential fixed capital, as reported by the Bureau of Economic Analysis, divided by the total residential population of the U.S., as reported by the Bureau of the Census. The capital stock figures are dated to correspond to the model's timing convention: The BEA reports the capital stock as end-of-year figures which corresponds to k_{t+1}, the capital available for use in production at the beginning of the following year.

[13]The slowdown and subsequent increase in capital growth are the subject of recent analyses by Ho, Jorgenson and Stiroh (1999) [the slowdown] and Tevlin and Whelan (1999) [the increase].

section describes a more carefully calibrated and fitted set of simulation experiments designed to evaluate the importance of the model's dynamics for explaining growth patterns in the post WWII U.S. economy.

Simulated Dynamics for the U.S. Economy

Taking the model's implications more directly to the data, in this section I describe and report the results of a procedure for simulating the responses of a fully calibrated version of the model to data-based proxies of the model's growth shocks. The procedure requires first that a model-consistent set of data be compiled. From this data, empirical counterparts for the model's key variables are constructed, and time series for neutral and investment embodied technology growth are derived.

In order to identify the stochastic-trend components of these series, I append to the model a limited-information structure in which agents must solve a signal-extraction problem to distinguish trend shifts from transitory components. This structure naturally lends itself to the application of a Kalman filter for identifying trend components and describing their time series properties.[14]

Using these measures of growth shocks, I carry out simulations of the model, and evaluate its ability to match the data.

[14]A similar information structure was assumed in Kydland and Prescott (1982).

Measuring Investment-specific Technological Change

In order to identify growth-trend shocks and to simulate their effects on growth patterns in the U.S. economy, careful data measurement and model calibration are necessary. In particular, the presence of investment-specific technology growth in the model requires special attention to relative prices and, of course, to the measurement of quality-improvement in capital goods.[15]

As Greenwood, Hercowitz and Krusell (1997) demonstrated, it is important to account for the role of Q in the model as a relative price. The model represents output, consumption and investment as sharing a common price, with Q representing the price of new, higher-quality capital goods relative to this numeraire. Hence, it is appropriate to construct empirical measures of output and investment by deflating their nominal values by a consumption price index.

The relevant measure of consumption is taken to be the total of nondurable goods and services, obtained by chain-weighting these two components of personal consumption expenditures from the National Income and Product Accounts. The chain weighted price measure corresponding to this series is used to deflate nominal variables for output and investment.[16] Consequently, real output is constructed as the ratio of nominal private business sector output to this consumption price index. This particular definition of output is selected because it corresponds to that used for a broad measure of

[15] A more detailed description of the data is included in an Appendix and in Pakko (2001).

[16] The consumption measure includes only nondurables and services in order to abstract from issues of quality improvement in consumer durables.

labor productivity. The model counterpart to investment is taken to be total private nonresidential fixed investment (nominal divided by the consumption price index).

Another important consideration in constructing empirical proxies for the model's variables is the appropriate measurement of quality-improvement in new capital goods. Previous analyses have based estimates of quality change on data from the detailed analysis of Gordon (1990). Unfortunately, Gordon's data set extends only through 1983. More recent papers on investment-embodied technology have extended the data somewhat by adding an estimate of the trend in unmeasured quality growth to the official investment data, making adjustments for improvements in the BEA's measurement of computer prices.[17] As time passes, however, changes in the composition of investment and changes in the BEA's methodologies for measuring quality change have made such a simple extrapolation more tenuous.

To update Gordon's data set for use in this paper, I took a disaggregated approach, extrapolating trend rates of unmeasured quality-change sector-by-sector. The general methodology involved extrapolating each of Gordon's 22 main investment categories forward through the year 2000 using trend estimates of the average growth rate of unmeasured quality change based on the last 10 years of his sample period.[18] For several of the categories, changes in the BEA's definitions and methodologies for measuring quality improvement required special attention and adjustment (see the Data Appendix

[17]For example, Greenwood, Hercowitz and Krusell extend the Gordon data through 1990 by subtracting 1.5% from the growth rates of price indices for all categories of investment spending except computers.

[18]Unmeasured quality change is extrapolated using only the latter part of Gordon's sample period, rather than using full-sample averages, because he found that unmeasured quality improvement was far more prevalent in the earlier part of the post-WWII era,

for more details). For example, the category of "office, computing and accounting machinery" was divided into separate categories for computers and other office equipment, computer software was included as an investment expenditure in 1999, and hedonic price indices have been introduced to directly estimate quality improvement in several components of the investment data.

Moreover, in 1996 the BEA adopted a chain-weighting methodology for aggregation, an approach similar to the Törnqvist-index that Gordon applied and recommended as an appropriate way to aggregate components that experience large changes in relative price and quality. To be consistent with the current BEA methodology, I apply Gordon's ratios of adjusted to official data (extrapolated through 2000) to contemporary data and construct a chain-weighted aggregate of the resulting series. With the inclusion of software, this aggregate represents a fully quality-adjusted version of the BEA's contemporary definition of private investment in equipment and software.

To extend the definition of investment and capital to include nonresidential structures, I use the long-run estimate of Gort, Greenwood and Rupert (1999) that unmeasured quality change in structures averages an annual rate of 1 percent. After applying this adjustment to produce a quality-adjusted real-price decomposition, the nonresidential structures component is aggregated with the Gordon-adjusted data on equipment and software by chain-weighting.

The end result of this procedure is a decomposition of nominal private nonresidential fixed investment into quality-adjusted price and quantity components. The price component is used to construct Q as the ratio of the consumption price index to the quality-adjusted price index for investment.[19]

The real component corresponds to $Q \times I$, the relevant measure of quality-adjusted gross investment in the capital accumulation equation (3). Hence, this measure is used to construct a measure of the capital stock that reflects investment embodied technological progress. Using data from the BEA's Fixed Reproducible Wealth accounts I calculated a series of depreciation factors, backing out δ using the official data on real stocks and investment flows.[20] After adjusting for the level of the series in 1948, I used these discount factors, together with the quality-adjusted data representing $Q \times I$, to construct an adjusted measure capital stock.[21]

Finally, a measure of neutral technological progress can be calculated as a Solow residual, using calibrated values for labor and capital shares and data series for output, quality-adjusted capital, and employment. For a measure of employment, I use the index of Total Hours for Private Business Sector employees as used by the BLS for constructing labor productivity statistics.

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[19] One further adjustment was made to the Q series: The measure directly derived from Gordon's data shows a sharp upward then downward movement in 1974-75. As Gordon points out, this pattern is largely attributable to the fact that one of Gordon's main data sources was the Sears catalog, and that he used an issue published in April 1974, two months before the lifting of wage and price controls. Because this fluctuation in the data appears unlikely to truly reflect a technological development, I smoothed this hump in the data by interpolation.

[20] Because the capital stock data are aggregated using chain-weighting, this depreciation factor for the total capital stock includes the effects of price and compositional changes (see Whelan 2000a). I use these factors, rather than a fixed depreciation rate, to approximate the chain-weighting scheme.

[21] The level-adjustment used to initialize the series, described in more detail in the data appendix, is based on the relative magnitudes of the official and quality-adjusted investment series at the beginning of the sample period and an assumption that investment/capital ratios were near their steady state values. It suggests that the appropriate initial value for the capital stock is approximately one-third of the official level (in chain-weighted 1996 dollars).

All real values (except the technology indices Z and Q) are converted to per capita magnitudes using Total Resident Population of the U.S., as reported by the Census bureau. The full data set covers the period 1948 through 2000.

Figure 6 shows the growth rate of the adjusted capital stock measure. Comparison with Figure 5 reveals that the adjusted growth rate follows the same general pattern as the conventional measure, but at a higher rate – about 2.2 percent, on average.

Figure 7 illustrates the behavior of the measures of neutral and investment-embodied technological progress, Z and Q. In terms of indexed levels, as shown in the upper panel of Figure 7, significant changes in trend growth of these variables are apparent. From at least 1950 through the 1960s, neutral technology growth averaged about 1.6 percent, but the series has been basically flat ever since. Investment specific technology growth averaged about 2.7 percent over the entire sample. From the 1950s through 1973, Q grew at a rate of about 2.2 percent. From 1974 through 2000 Q-growth averaged 3.2 percent. More recently, in the period from 1983 through 2000, the average growth rate has been 4.0 percent.[22]

The actual year-to-year growth rates shown in the lower panel of Figure 7 reveal that there is quite a bit of variation in these series beyond that which could be reasonably attributed to changes in growth trends, however. In order to extract a trend component from these data series, I turn to a limited-information extension of the model.

[22]Given the calibration of factor share parameters, equation (6) and the data on Q and Z imply that the average the average rate of investment-specific growth accounts for about 52% of output and productivity growth over the entire sample period. From 1984 through 2000 the contribution is much larger, accounting for over 80% of potential trend growth.

A Limited-Information Setting

As described in equation (4) above, each of the technology variables is assumed to include stochastic growth trends, *G*, and cyclical components, *v*: Suppose now that each of the v_i and γ_i, in turn, is assumed to follow an independent AR(1) process:

$$\gamma_{it+1} = \rho_{\gamma i}\gamma_{it} + \varepsilon_{it+1} \quad and \quad v_{it+1} = \rho_{vi}v_{it} + u_{it+1}, \quad i = z,q \tag{9}$$

Together with equation (4), this structure implies that the growth rate of each technology variable follows an ARMA(1,1) process. The growth-rate shocks comprise the AR component, while the first-differences of the v_i contribute moving average components of the model's growth rates.

Now suppose that individuals can observe the variables *Q* and *Z* but cannot precisely distinguish growth shocks from level shocks. Instead, they must solve a signal extraction problem given some knowledge (or assumptions) about the underlying distributions and time series properties of the underlying growth-shock and level-shock processes.

Such a structure readily lends itself to analysis using a Kalman filter.[23] The Kalman filter is essentially an algorithm for sequentially updating linear least-squares forecasts of the state vector of a model, which in this case comprises a growth component and a stationary, transitory component, each of which follows an AR(1) process. Given an observed growth rate, previously estimated values for the state variables, and an estimate of the relative contributions of growth shocks and level shocks to the overall variance of

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[23]For more formal descriptions of the Kalman filter and its application to this type of problem, see Watson (1989) and Hamilton (1994), Chapter 13. The particular details of its application to this problem are described in Appendix B.

technology growth, the Kalman filter provides a procedure for constructing rational inferences about the relative magnitudes of decomposition of current shocks.

Rather than calibrating the values of the autoregressive parameters and autocovariance matrices of the shock processes, I use the Kalman updating equations to construct a sample log-likelihood function. Iterating on the Kalman filter procedure, standard numerical methods are used to maximize the log-likelihood function, yielding estimates for parameter values and growth-rate decompositions that best fit the data.

The procedure produces the following estimates for the autoregressive parameters:

$$\rho_{\gamma z} = .925, \qquad \rho_{vz} = .738$$

$$\rho_{\gamma q} = .873, \qquad \rho_{vq} = .950\ .$$

The estimated variance-covariance matrices for the two technology variables imply that changes in growth trends account for about 27.5% of the variance of Z_t, and about 13.7% of the variance of Q_t.

The Kalman filter algorithm produces estimates of the state variables (γ_i and v_i) using information from period t and earlier. These estimates are used for the current growth trends – the γ_{it} in equation (8). The remaining portion of the technology growth rates are attributed to the first-differences of the level-shocks.[24]

The growth-trends relevant for capital accumulation decisions are expected future rates. However, the time-t estimates of the trend – based only on current and past

[24]As described in Appendix B, the state vector includes v_t and v_{t-1} yielding direct measures that can be used to construct the level-shocks.

information – amount to something of a backward-looking, adaptive algorithm.[25] In order to incorporate the forward-looking expcted growth trend estimates, the growth shocks are constructed from the trend estimates the use information though t+1; that is, in assessing future growth trends, agents are assumed to have perfect foresight one period into the future.

Figure 9 shows the estimates of trend-components in that this procedure produces from the Q and Z growth series. These growth trends each contain several notable fluctuations over the period, but at lower frequency and with lower variance than the underlying growth rate series.

Estimates of the growth shocks are backed out from these series using equations (9) and the autoregressive parameter estimates found by the maximum likelihood procedure. Innovations corresponding to the trend-stationary level-shocks are similarly constructed from the state variables, ν_{it}, which track the fluctuations in growth rates that are not accounted for by the trend estimates.

With a complete set of estimated shocks available, the model can be simulated to construct paths for the model's variables, and then to compare their behavior to counterparts in the data.

Simulation Results

In order to delineate the roles of growth shocks and level shocks, and of neutral and investment-specific technology trends, I conduct a series of simulations that builds in

[25]Moreover, the use of annual data and the model's convention of a one-period lag between investment decisions and the availability of productive capital raise time-aggregation issues that are relevant.

complexity.   In each of the simulations, the starting-period is 1948, the first shocks occur in 1949, and the model's results are reported for the period 1950-2000.

Neutral Technology Growth-Trend Effects

The first simulation is one in which only neutral technology growth is subject to a variable growth-trend–corresponding most closely to the example of the Solow growth model. The contribution of investment-specific growth to the simulation is solely in its long-run average growth rate (and its effect on the average growth rate of capital). Dynamics are driven entirely by the stochastic growth-trend component of Z_t and the model's endogenous responses to the growth shocks implicit in that trend. Figure 9 shows the growth paths of the model's variables in this case.

For several of the model variables, Figure 9 suggests that this simulation experiment generates trends that fit the data reasonably, but accounts for little of the year-to-year variation in growth rates. For the growth rates of capital and investment, however, the model generates simulated growth paths that fit some of the prominent fluctuations in the data rather well. The variance of the simulated series for investment growth is also notably more consistent with the data.   The model generally matches peaks in investment and capital growth that occurred around the time of the productivity slowdown in the late 1960s and early 1970s. The simulated growth paths also show downturns in investment and capital growth in the early 1980s and early 1990s, corresponding to noticeable increases in $\gamma_{zt,}$.

Over the period of the past 10 to 15 years, however, the simulated capital growth rate fails to match either the depth of the downturn in the early 1990s or the rapid increase in growth over the remainder of the decade. The model also under-predicts investment growth during the 1990s.

Table 1 presents some quantitative measure of the fit for this simulation experiment. The first column shows the correlation between actual and simulated values, and the next two columns show the standard deviations of actual and simulated growth rates over the sample period. The correlations between actual and simulated series are all positive, and in most cases, significantly so. The standard deviations of actual and simulated data are generally of the same order of magnitude, but the model tends to under-predict the variability of output, productivity, work-effort and investment.

The remaining columns of Table 1 decompose the correlations between actual and simulated data into components reflecting the role of the exogenous growth trends and the model's endogenous dynamics. This serves to reveal the importance of the model's internal propagation mechanism in generating the correlations in the first column.

The additive construction of the simulated growth paths in equation (8) implies that the correlations between actual and simulated data series can be represented as a weighted average of the correlation between the data with the growth trend, and the data with the model's impulse-responses. In particular,

$$corr(x_t, \hat{x}_t) = \frac{sd(g_{xt})}{sd(\hat{x}_t)} corr(x_t, g_{xt}) + \frac{sd(\hat{r}_{xt} - \hat{r}_{xt-1})}{sd(\hat{x}_t)} corr(x_t, \hat{r}_{xt} - \hat{r}_{xt-1}) \quad (10)$$

The decompositions suggest that for consumption, output, and productivity, the positive relationship between actual and simulated growth rates is solely attributable to the growth trends themselves. On the other hand, the model's internal propagation mechanism explains almost all the correlations for investment, capital, and labor. For labor, which has no trend growth, the model's endogenous dynamics explain all of the relationship between the simulated and actual series. For investment and capital growth, the endogenous components account for over 80% of the full correlations. These results tend to support a role for adjustment of the capital/labor ratio to changes in the trend growth rate of technology, as represented here in the Solow residual series.

Investment-Specific Technology Growth-Trends

To assess the role of technology growth that is capital-embodied, the second simulation adds a stochastic growth trend for investment-specific technology growth. The underlying trend is modeled to incorporate changes in both neutral and embodied growth, and the model's endogenous dynamics reflect responses to both types of growth-trend shocks.

Figure 10 shows the growth paths generated by this simulation. The patterns are quite similar to those of the simulation including only neutral technology growth-shocks. As discussed earlier, the growth relationships in equations (5) and (6) imply that a given proportionate change in investment-specific technology growth has a smaller effect on output and productivity growth, so it is not surprising that there is little apparent effect of incorporating investment-specific growth-trend shocks for many of the model's variables.

There are some clear differences between the simulations illustrated in Figures 9 and 10, however. The increase in investment-specific technology growth in the mid-1950s gives rise sharpens the a decline in capital growth early in the sample period, improving the correspondence between the simulation and the data. The subsequent slowdown reinforces the peak in investment and capital accumulation growth around

1970, and also exaggerates the decline in the early 1980s as both types of technology growth showed signs of increasing.

While the capital-stock growth rate shows acceleration in the late1990s, it still fails to capture the sharp decline earlier in the decade. Investment growth does show a sharper decline in 1991, and in 1995, however. At least in part, there is an obvious explanation for this apparent anomaly: the rapid pace of technological change during the 1990s was associated with higher average rates of depreciation–particularly so for computers.[26] In the model, however, depreciation is assumed to be constant. The growth rate of investment is consistent with a decline in capital-stock growth in the early 1990s, but the magnitude of the decline in capital growth was apparently augmented by increasing rates of depreciation.[27]

Table 2a documents the correlations of actual with simulated data when investment-specific growth-shocks are included. Comparing the correlations to those resported in Table 1, it is apparent that the addition of investment-specific growth shocks does little to quantitatively enhance the correspondence between actual and simulated growth rates. The correlations are slightly higher for capital and productivity growth, and slightly lower for investment and work-effort. Note that the correlation between capital stock growth and the underlying trend is now negative, with the endogenous dynamics explaining all of the correspondence between actual and simulated series. The relative contributions of exogenous trend growth and endogenous model dynamics are generally

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[26]Some implications of rapid depreciation and obsolescence of computing technology are explored by Whelan (2000b).

[27]This observation suggests the efficacy of including variable capital-utilization and depreciation, as in the model of Greenwood, Hercowitz and Huffman (1988).

similar to those found for neutral growth shocks alone, although the negative correlations between actual and simulated series for productivity, output and consumption are now smaller in absolute value.

Table 2b decomposes the model's endogenous component into responses attributable to the two type of growth trends separately (similar to the decomposition described in equation 10). The first column reports the correlations of actual series with the endogenous component of the simulated series, as shown in the final column of Table 2a, with the remaining columns separating the roles of the two type of shocks. The contribution of investment-specific growth shocks is clarified by this decomposition. Most notably, the endogenous responses to these capital-embodied growth shocks are all positively correlated with the actual series, accounting for the improvement in fit for productivity, output and consumption. Although investment-specific technology growth shocks give rise to relatively smaller changes in long-run productivity growth, the impulse response functions in Figure 4 show that the impact-responses are sharper for this type of shock. Evidently, these initial responses to changes in the underlying growth trend match the data in such a way as to improve the overall fit of the model with respect to output and productivity.

When both types of shocks are included in the analysis, the simulation results continue to be supportive of a role for adjustment of the capital/labor ratio in response to growth-trend changes. Other aspects of the model simulations are less convincing, with negative correlations between the data and the endogenous components of the model simulation. In terms of verifying the theory examined in this paper, the results for labor productivity might appear particularly problematic in light of the model's prediction that productivity growth responds with a lag to changes in underlying technology growth trends.

However, the decompositions between underlying trend and endogenous dynamics reported in Tables 1 and 2 might not be the best way to assess the ability of the model to explain productivity growth. The most important aspect of the relationship between growth shocks and productivity is not in the initial impact response that would feature prominently in contemporaneous correlations, but in the gradual convergence of productivity growth to trend. Alternative measures of the correlations between actual and simulated productivity growth are revealing in this regard. For example, the correlation of productivity growth minus trend with the model's endogenous growth dynamics (a common RBC-evaluation metric) is positive at 0.203. Similarly, the partial correlation between actual and simulated series, holding the growth trend constant, is small but positive (0.149). These results suggest that the negative contemporaneous relationship between trend and endogenous responses, which tends to smooth the simulated productivity series relative to trend, is largely responsible for the negative results in the decompositions of Tables 1 and 2.

Figure 11 illustrates this relationship.[28] The simulated series for productivity growth appears as a smoothed version of the exogenous trend. Some of the higher-frequency variations in the trend series that correspond to fluctuations in the data are ironed out by the model's dynamics, leaving what appears as a smoother trend line. For

[28]In Figure 11, the underlying trend and simulated productivity series are adjusted slightly (approximately 0.2%) so that simulated and actual series have equal means. No effort was made to account for differences in the first moments of actual and simulated series, and for the most part, the measures of fit used to evaluate the simulations are invariant to differences in means.

most sub-sample periods, the simulated series fits the data better than the raw trend in terms of root-mean-squared error.

As suggested by the previous analysis of the model's dynamics, the simulated series is above trend when technology growth is slowing, and above trend when technology growth is rising. In particular, simulated productivity growth is lower than that predicted by technology trends alone over most of the 1980s and 1990s, as investment-embodied growth-trend shocks have gradually ratcheted-up the underlying trend, while simulated productivity growth has lagged the trend implied by technology growth alone.

Shocks to the Level of Technology

The final simulation experiment adds the effects of level-shocks to the analysis. Figure 12 shows the results of this simulation, which now includes the full panoply of shocks identified by the Kalman-filter decomposition. Table 3a reports the correlations between the actual and simulated growth rate series for this case.

The inclusion of level shocks increases the correlations significantly for output, productivity and consumption, in particular. Evidently, much of the high-frequency variation in the growth rates of these series is related to the short-term effects of the RBC-type shocks to the level of technological change With both level shocks and growth shocks included, the standard-deviations of the data and simulations of these series are also very close. Investment and capital growth are now far more variable in the simulations than in the data.

Table 3b decomposes the contribution of endogenous model responses into components attributable to the growth-shocks and the level-shocks. Clearly, the transitory level-shocks account for much of the short-run variability of output, consumption and productivity growth. For investment and work effort, the level-shocks account for about half of the overall correlation between the data and the model's endogenous dynamics. Note that for capital stock growth, the inclusion of level-shocks induces greater volatility in the simulated series without making any positive contribution to the overall correlation of the simulated series with the data.

The overall conclusion to be drawn from these simulation experiments is that changes in growth trends do appear to contribute significantly to the dynamics of capital accumulation, investment and – to a lesser extent – work effort. The growth trends, and the dynamics they generate, explain much of the long-run movements in growth rates for other model variables. However, for consumption and output growth in particular, transitory RBC-type level-shocks explain most of the year-to-year variability in growth patterns.

Implications For the Future: Outsample Forecasts

As observed above, the relationship between the technology trend and measured productivity growth implied by the model is such that the simulated productivity growth path tends to be higher than the underlying trend when the trend is falling, and above it when the trend is rising. Since at least the mid-1999s, a rising trend in technology growth has meant that productivity has lagged behind the trend.

The implication of this observation is that the technological advances of the past two decades have contributed to a rising growth rate of labor productivity, but that higher productivity growth has yet to catch up to the trend implied by underlying technology. That is, the fundamental model dynamics suggest that we have yet to observe the full productivity-enhancing effects of recent technological progress.

Table 4 reports the results of outsample simulations, providing estimates of the model's implications for future productivity growth. In order to abstract from small differences in long-run average growth rates among the simulations and the data, the productivity growth rates shown in Table 4 are reported relative to average growth over the period 1973-2000. In the data, productivity growth was slightly more than 0.1% below this average over the first 23 years of this period, and nearly three-quarters of a percentage point above the average during the past five years.

Simulated averages for productivity growth are shown for each of the three simulation experiments described above. In the simulations including only growth shocks, the change in average growth rates between the 1973-1995 and 1996-2000 are both smaller than shown in the data, although the simulation including investment-specific shocks shows an increase that is relatively close to actual experience. Each of these simulations suggest that productivity growth over the next five to ten years will be above the 1996 average – by ½ a percentage point or more. The simulation that includes transitory level-shocks shows an increase in the 1996-2000 period that is larger than the data, as part of the increase in this case is due to a series of positive innovations in technology. As these transitory, cyclical components dissipate over time, the increase in productivity growth predicted for 2001-2010 is smaller than for the simulations including only growth shocks. Nevertheless, this version of the model also suggests that the productivity gains of the 1990s are not entirely transitory, but are predicted to be sustained into the future.

Conclusions

Current prospects for economic growth in the U.S. are fundamentally related to the question of whether or not the rapid rate of expansion of the late 1990s signaled an increase in the underlying trend rate of growth. Speculation about shifting growth trends has been an important topic in macroeconomics since well before the recent acceleration of growth. Indeed, explaining the apparent productivity slowdown of the early 1970s has proven to be one of the most challenging issues faced by macroeconomists in recent years.

Despite the apparent practical importance of changes in growth trends, however, there has been little fundamental analysis of how a change in underlying technology growth would be expected to work itself through the economy from a simple general equilibrium perspective. This paper addresses that question, modifying a basic RBC-type model to incorporate stochastic growth trends.

The model predicts that a shift in the underlying trend rate of technology growth has potentially important implications in terms of adjustment dynamics: Changes in growth trends give rise to incentives to alter the mix of capital and labor in the production process, resulting in an extended period during which measured productivity lags behind the potential trend implied by technological progress. Simulations of post-WWII U.S. economy reveal that the model's implied dynamics are consistent with some key features of investment growth and capital accumulation over the sample period. The model also generates a path for employment growth that qualitatively replicates much of the growth variation in that key variable over the sample period.

Not surprisingly, this single propagation mechanism is insufficient for generating artificial economic growth paths that match the data along all dimensions. In particular, the simulations suggest that much of the short-term, year-to-year variation in the growth rates of consumption, output and labor productivity are more closely associated with transitory fluctuations in the level of technological change around its growth trend.

When simulated out of sample, the model suggests that the increases observed in productivity growth over the late 1990s are partly cyclical, but largely attributable to an acceleration in underlying technology growth. Because of the lagged relationship between trend changes in technology and productivity growth, the model's dynamics suggest that the recent acceleration in economic growth represented only a transitory phase in this process. The model predicts that the trend rate of productivity growth will remain strong, or even accelerate, over the horizon of the next five to ten years.

Appendix A: Data

Basic Data Set: Summary

The full sample period is 1947-2000. Except where otherwise noted, data are from the National Income and Product Accounts, available from the Bureau of Economic Analysis.

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 1947 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 (1996 dollars) 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.

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 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 it's 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 D1 shows trends in the drift ratios calculated by Gordon for individual components of investment spending. The table is organized by the contemporary 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 D1 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.

Applying Gordon's Adjustments to Contemporary Data

In order to apply Gordon's quality adjustment to contemporary 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 1983-2000 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 2000 using the growth rates in the second column of Table D1. The base period for the drift ratios is updated to 1996, to match the present NIPA convention, 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 suggested 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.[29] 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.

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

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.[30] 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"[31] 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

[30] Moulton and Seskin (1999).

[31] Gordon, p. 538.

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.[32] In the comprehensive revision of 1991, this change was carried back to years prior to 1984.[33] This change altered both the nominal and real data series on investment spending for automobiles, and largely eliminated the "spurious decline" in the 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.[34]

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[35] 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.[36]

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[32] Fox (1987).

[33] Fox and Parker (1991).

[34] 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.

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

[36] 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.

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 (see shaded box). 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.

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 utilize 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 of 1947-2000, then construct an adjusted real series expressed in 1996 chain-weighted dollars. 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.

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 follows the methodology of the BEA's estimates of fixed reproducible wealth.[37]

The BEA uses a perpetual inventory method with geometric depreciation – the same general form as in the capital accumulation equation in the model [equation (3)]. Each year's capital stock is constructed as he sum of un-depreciated capital from the previous year plus gross investment. 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 that new assets depreciate at a rate equal to one-half of the annual depreciation rate on existing assets:

$$K_t = (1-\delta)K_{t-1} + (1-\delta/2)I_t \tag{A1}$$

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

[37]See Katz and Herman (1997).

implied depreciation factors.[38] 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.

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

$$qi / k = \gamma_k - (1 - \delta). \qquad \text{(A2)}$$

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:

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

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 the steady-state requirement that output and capital grow at the same rate (in the absence of explicit quality improvement). Taking 1948 to be the base year, the ratio of the quality-adjusted investment series to the official series is 0.441. Average growth rates over the sample period are γ_y=1.0228 and γ_q=1.0276. Hence, the implied ratio of k^{ADJ} to k^{NIPA} is approximately 0.34.

[38]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

APPENDIX B: Application of the Kalman Filter

This appendix describes the application of the Kalman filter procedure to the signal extraction problem outlined in the limited-information version of the model.[39] The Kalman filter is used to decompose each of the technology growth-rate series into trend and transitory components. The procedure is described here in terms of the investment-embodied technology variable, Q_t. The neutral technology index is treated in an identical manner.

Letting $x_t = \ln(Q_t\text{-}Q_{t-1})$, an appropriate state-space representation of the growth rate of investment-embodied technological change described by equations (9) can be written compactly in the form:

Observation Equation: $x_t = H'\xi_t$

State Equation: $\xi_{t+1} = F\xi_t + v_{t+1}$

with

$$\xi_{t+1} = \begin{bmatrix} \gamma_{qt+1} \\ v_{qt+1} \\ v_{qt} \end{bmatrix}, \quad v_t = \begin{bmatrix} \varepsilon_{qt} \\ u_{qt} \\ 0 \end{bmatrix},$$

$$H = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}, \quad and \quad F = \begin{bmatrix} \rho_{\gamma q} & 0 & 0 \\ 0 & \rho_{vq} & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

[39] A thorough description of the general Kalman filter procedure can be found in Hamilton (1994), Chapter 13.

The variance-covariance matrix of underlying shocks is:

$$W \equiv E(v_t v_t') = \begin{bmatrix} \sigma^2_{\varepsilon q} & \sigma_{\varepsilon uq} & 0 \\ \sigma_{\varepsilon uq} & \sigma^2_{uq} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

Given initial values for the mean and variance of the state vector, $\hat{\xi}_{1|0}$ and $P_{1|0}$,

estimates of the subsequent values of the state vector at each time t can be found as the update of a linear projection:

$$\hat{\xi}_{t|t} = \hat{\xi}_{t|t-1} + P_{t|t-1}H(H'P_{t|t-1}H)^{-1}(x_t - H'\hat{\xi}_{t|t-1}). \quad \text{(B1)}$$

The mean-squared error of the current forecast, $P_{t|t}$, can then be calculated iteratively from

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}H(H'P_{t|t-1}H)^{-1}H'P_{t|t-1}, \quad \text{(B2)}$$

where $P_{t|t-1}$ is the estimated mean-squared error of the previous period's forecast.

Given information at time t, the best t+1 forecast of the state vector, $\hat{\xi}_{t+1|t}$, can be

found by using the state equation as

$$\hat{\xi}_{t+1|t} = F\hat{\xi}_{t|t-1} + FP_{t|t-1}H(H'P_{t|t-1}H)^{-1}(x_t - H'\hat{\xi}_{t|t-1}) \quad \text{(B3)}$$

and the mean-squared error estimate of the one-period-ahead forecast is then given by

$$P_{t+1|t} = FP_{t|t}F' + W. \quad \text{(B4)}$$

As estimates of the current, transitory component of technology growth, the level shocks, *v*, are derived from the time-*t* elements of equation (B1). Similarly in constructing the simulated growth paths for model variables, the component representing the *current* underlying trend is taken to be the first element of the vector $\hat{\xi}_{t|t}$ from equation (B1).

Growth shocks, on the other hand, derive their relevance from their forward-looking, long-run effects. Consequently, the growth shocks are assumed to be represented by the first element of the state vector $\hat{\xi}_{t+1|t}$ given in equation (B3).

Moreover, time-aggregation issues arise in this context: using annual data and an accumulation specification that requires a full period for any investment to be incorporated into productive capital, it could be argued that this measure does not fully reflect information available to investment decision-makers. This is particularly so given the adaptive-expecations nature of the univariate Kalman filter algorithm. In order to better represent a forward-looking measure of expected growth trends, I assume that growth-trend estimates are constructucted using data from t+1 – that is, I assume one-period-ahead perfect foresight in the construction of growth-trend shocks.

Under general assumptions of normality, the distribution of x_t conditional on information available at time *t-1* is distributed normally with mean $H'\hat{\xi}_{t|t-1}$ and variance $H'P_{t|t-1}H$. It is therefore straightforward to construct a sample log likelihood function, which can be maximized numerically to estimate values for the parameters of the matrices F and W.

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Table 1:
Correlations of Actual with Simulated Data – Neutral Growth Shocks

x	Corr(x, x̂)	Standard Deviations (%)		Growth Trend			Endogenous Dynamics		
		sd(x)	sd(x̂)	Corr(x,γ)	sd(γ)/sd(x̂)	Contribution	Corr(x,r̂)	sd(r̂)/sd(x̂)	Contribution
K	0.442	1.217	1.544	0.056	0.970	0.054	0.366	1.058	0.387
I	0.566	6.173	5.267	0.316	0.284	0.090	0.562	0.846	0.476
N	0.538	2.409	0.465	0.000	0.000	0.000	0.538	1.000	0.538
Y/N	0.570	1.867	1.276	0.644	1.174	0.756	-0.409	0.454	-0.185
Y	0.313	2.808	1.452	0.382	1.032	0.394	-0.288	0.283	-0.082
C	0.087	1.182	1.252	0.291	1.197	0.348	-0.473	0.552	-0.261

Table 2a:
Correlations of Actual with Simulated Data – Neutral and Embodied Growth Shocks

x	Corr(x, x̂)	Standard Deviations (%)		Growth Trend			Endogenous Dynamics		
		sd(x)	sd(x̂)	Corr(x,γ)	sd(γ)/sd(x̂)	Contribution	Corr(x,r̂)	sd(r̂)/sd(x̂)	Contribution
K	0.480	1.217	1.372	-0.029	1.006	-0.029	0.389	1.308	0.509
I	0.505	6.173	6.148	0.340	0.226	0.077	0.477	0.898	0.428
N	0.515	2.409	0.555	0.000	0.000	0.000	0.515	1.000	0.515
Y/N	0.601	1.867	1.258	0.615	1.106	0.681	-0.157	0.507	-0.080
Y	0.330	2.808	1.413	0.410	0.985	0.404	-0.218	0.339	-0.074
C	0.098	1.182	1.257	0.347	1.107	0.385	-0.469	0.612	-0.287

Table 2b:
Contributions of Neutral and Embodied Growth Shocks to Endogenous Dynamics

x	Corr(x, r̂)	Neutral Growth Shocks			Embodied Growth Shocks		
		Corr(x,r̂)	sd(r̂)/sd(x̂)	Contribution	Corr(x,r̂)	sd(r̂)/sd(x̂)	Contribution
K	0.509	0.366	1.190	0.436	0.088	0.831	0.073
I	0.428	0.562	0.725	0.408	0.037	0.555	0.021
N	0.515	0.538	0.838	0.451	0.106	0.600	0.064
Y/N	-0.080	-0.409	0.460	-0.188	0.334	0.324	0.108
Y	-0.074	-0.288	0.290	-0.084	0.049	0.201	0.010
C	-0.287	-0.473	0.550	-0.260	-0.070	0.389	-0.027

Table 3a:
Correlations of Actual with Simulated Data – Growth Shocks and Level Shocks

x	Corr(x, $\hat{x}$)	Standard Deviations (%)		Growth Trend			Endogenous Dynamics		
		sd(x)	sd($\hat{x}$)	Corr(x,γ)	sd(γ)/sd($\hat{x}$)	Contribution	Corr(x,$\hat{r}$)	sd($\hat{r}$)/sd($\hat{x}$)	Contribution
K	0.320	1.217	1.667	-0.029	0.828	-0.024	0.428	0.803	0.344
I	0.458	6.173	12.031	0.340	0.116	0.039	0.430	0.972	0.418
N	0.458	2.409	1.109	0.000	0.000	0.000	0.458	1.000	0.458
Y/N	0.868	1.867	1.808	0.615	0.770	0.474	0.610	0.647	0.394
Y	0.849	2.808	2.559	0.410	0.544	0.223	0.794	0.788	0.626
C	0.434	1.182	1.657	0.347	0.840	0.292	0.233	0.612	0.143

Table 3b:
Contributions of Growth Shocks and Level Shocks to Endogenous Dynamics

x	Corr(x, $\hat{r}$)	Growth Shocks			Level Shocks		
		Corr(x,$\hat{r}$)	sd($\hat{r}$)/sd($\hat{x}$)	Contribution	Corr(x,$\hat{r}$)	sd($\hat{r}$)/sd($\hat{x}$)	Contribution
K	0.344	0.389	1.077	0.419	-0.070	1.071	-0.075
I	0.418	0.477	0.459	0.219	0.224	0.892	0.200
N	0.458	0.515	0.500	0.257	0.224	0.895	0.200
Y/N	0.394	-0.157	0.353	-0.056	0.573	0.786	0.450
Y	0.626	-0.218	0.187	-0.041	0.772	0.864	0.667
C	0.143	-0.469	0.464	-0.218	0.484	0.744	0.360

Table 4:
Simulated and Forecasted Productivity Growth Rates

	Productivity Growth Relative to 1973-2000 Average (Percent)			
	1973-1995	**1996-2000**	**2001-2005**	**2001-2010**
Data	-0.13	0.74	—	—
Neutral Growth Shocks	-0.08	0.35	0.80	0.87
Both Growth Shocks	-0.04	0.59	1.22	1.27
All Shocks	-0.22	1.01	1.05	1.03

Figure 1:
Growth Rate of Output per Hour, Business Sector

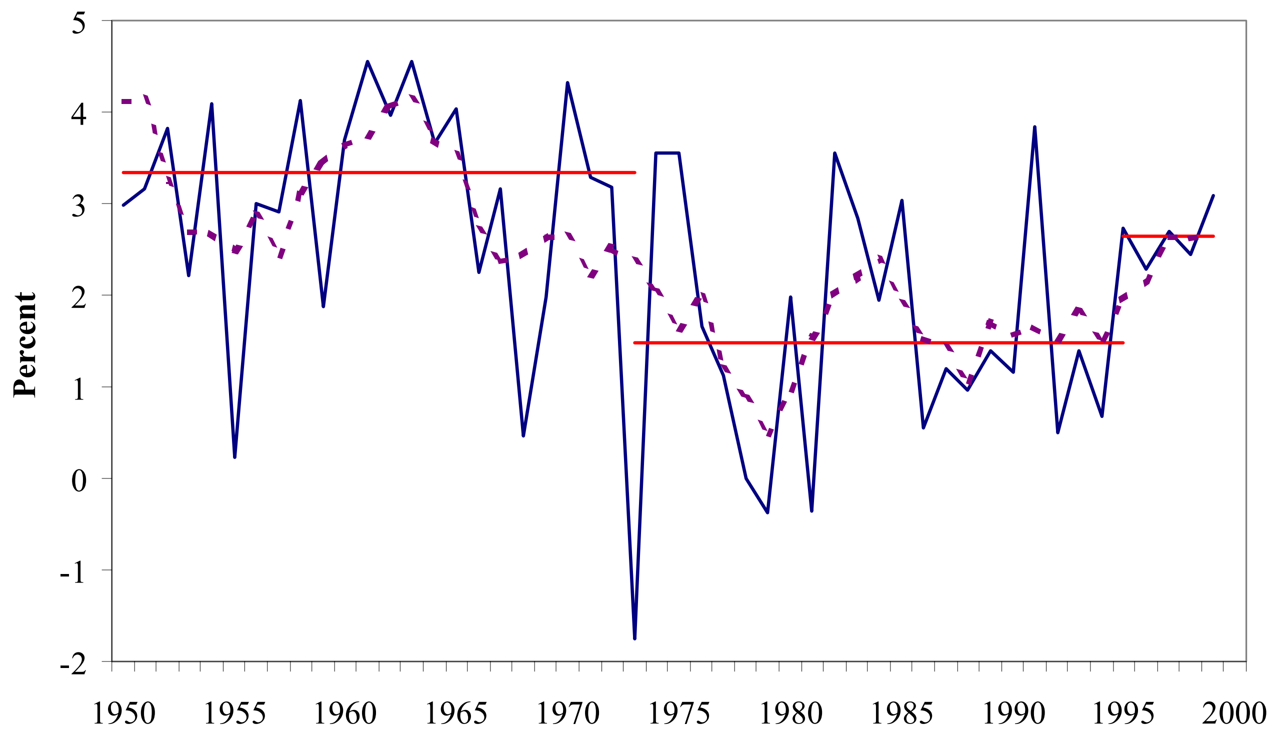


Figure 2:
A Textbook Solow Growth Model

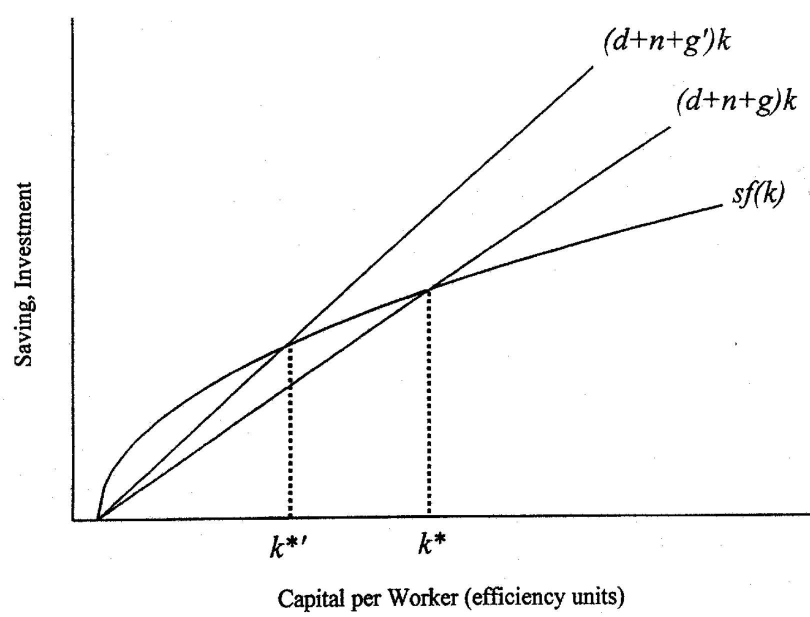


Figure 3:
Responses of Capital Stock and Consumption to a Technology Growth Shift

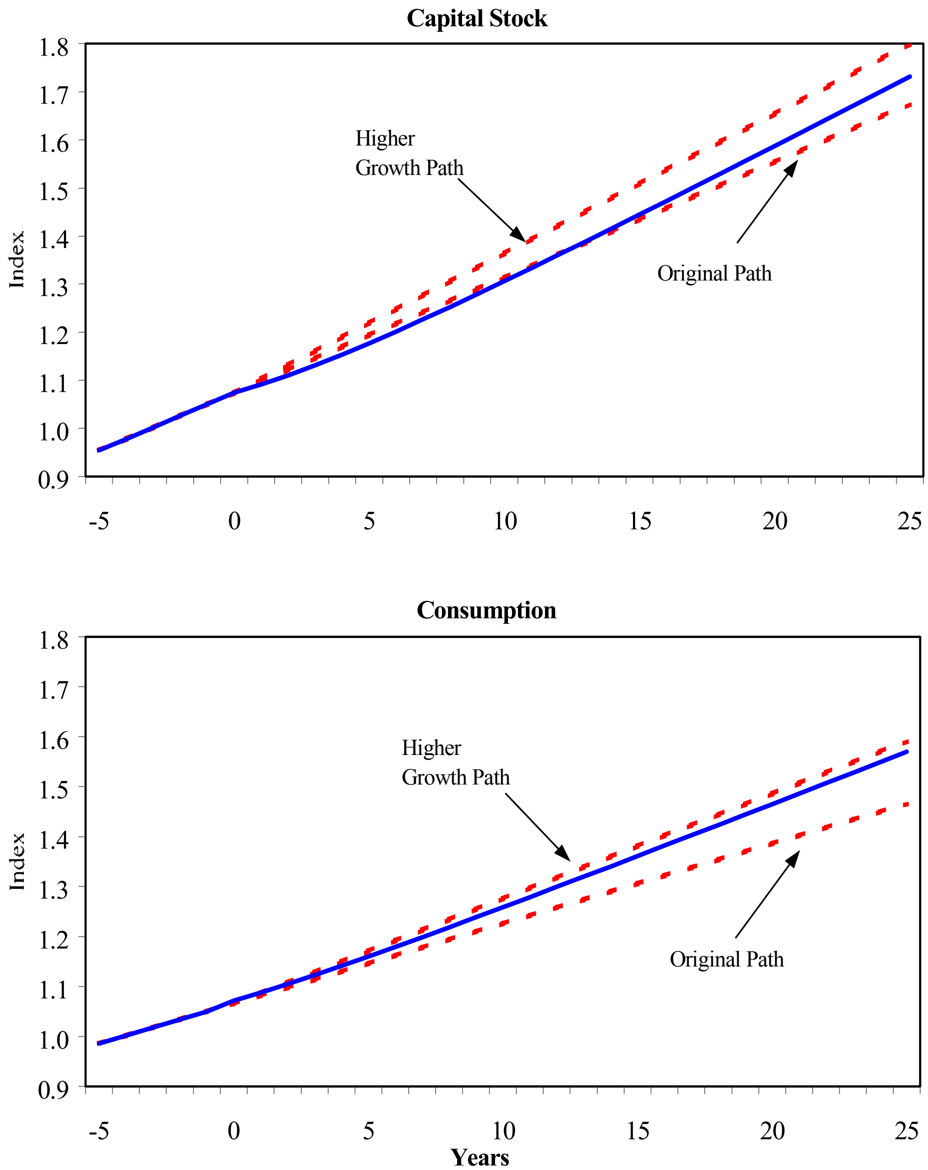


Figure 4:
Responses to Technology Growth Shifts

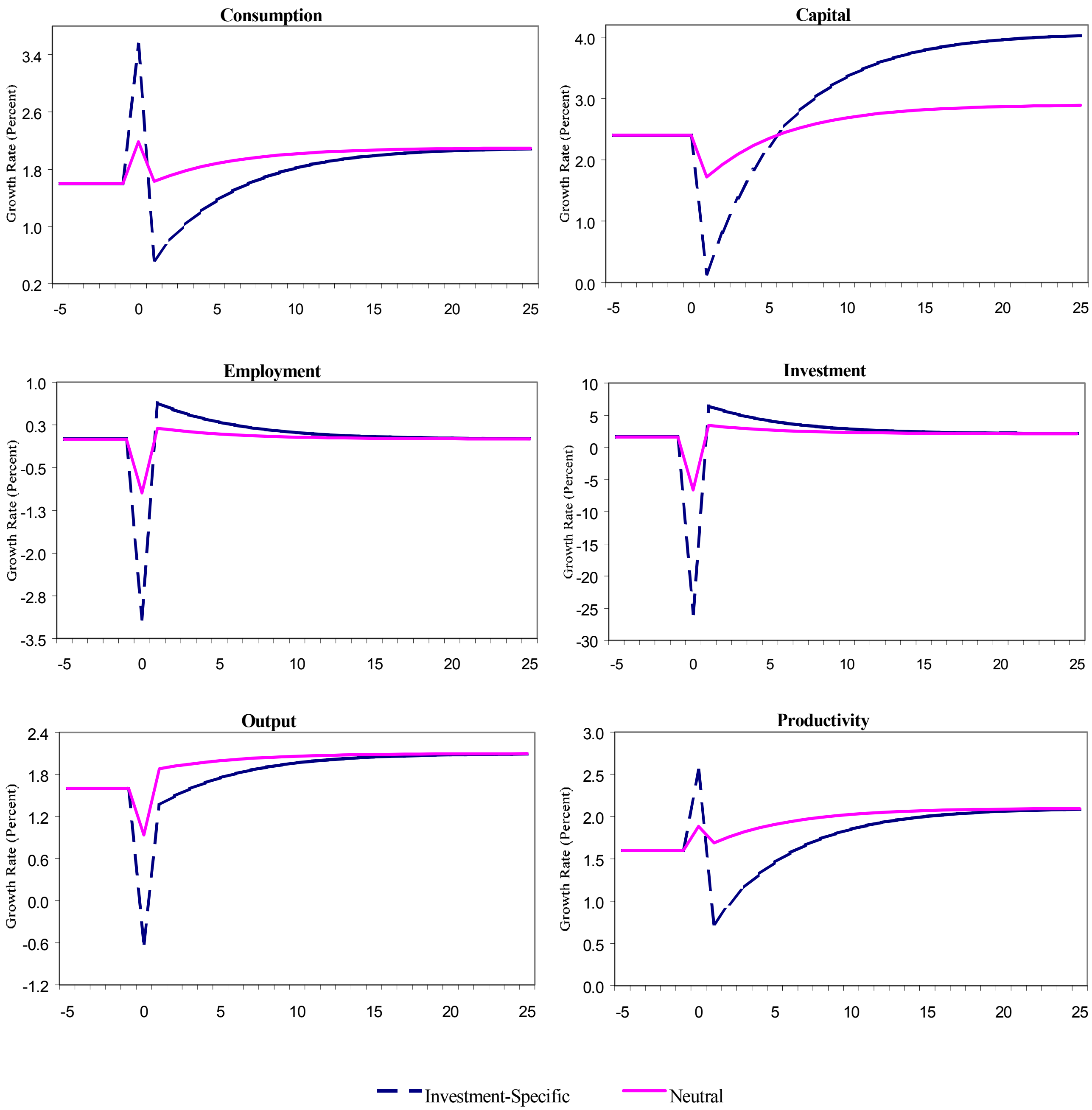


Figure 5:
Capital Stock Growth Per Capita

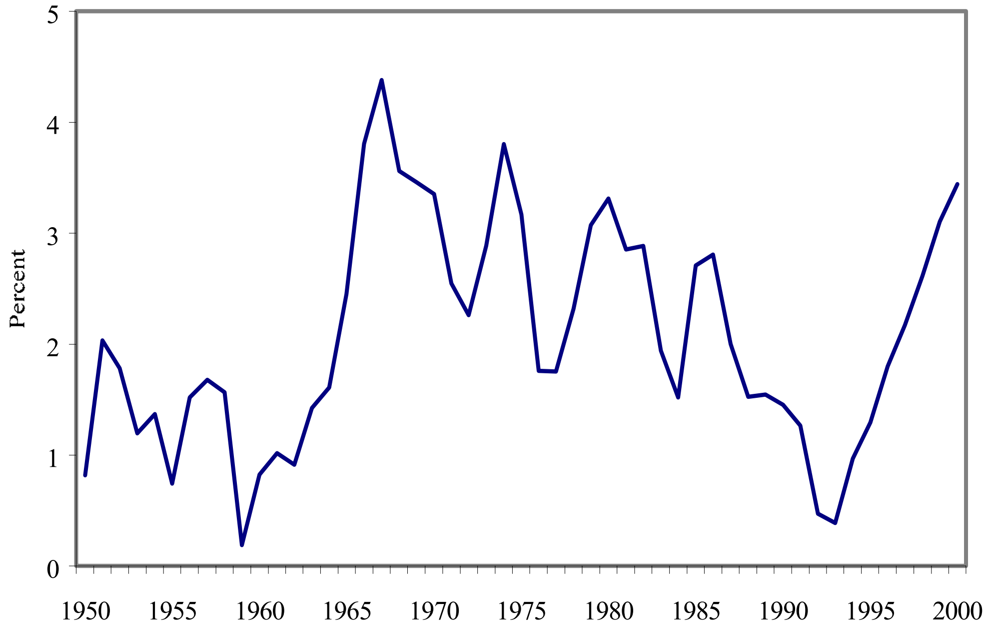


Figure 6:
Capital Stock Growth Per Capita,
Adjusted for Investment-Specific Technology

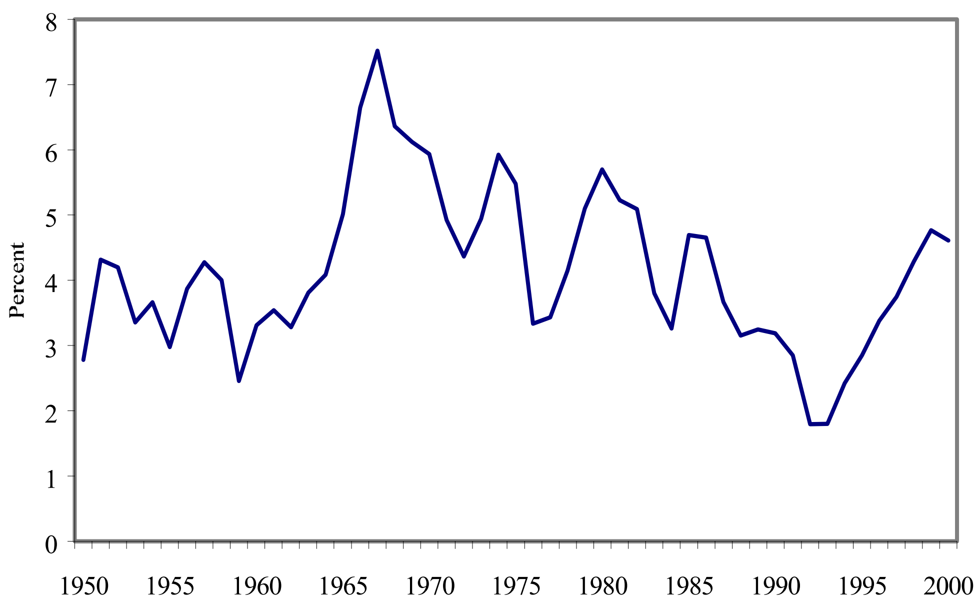
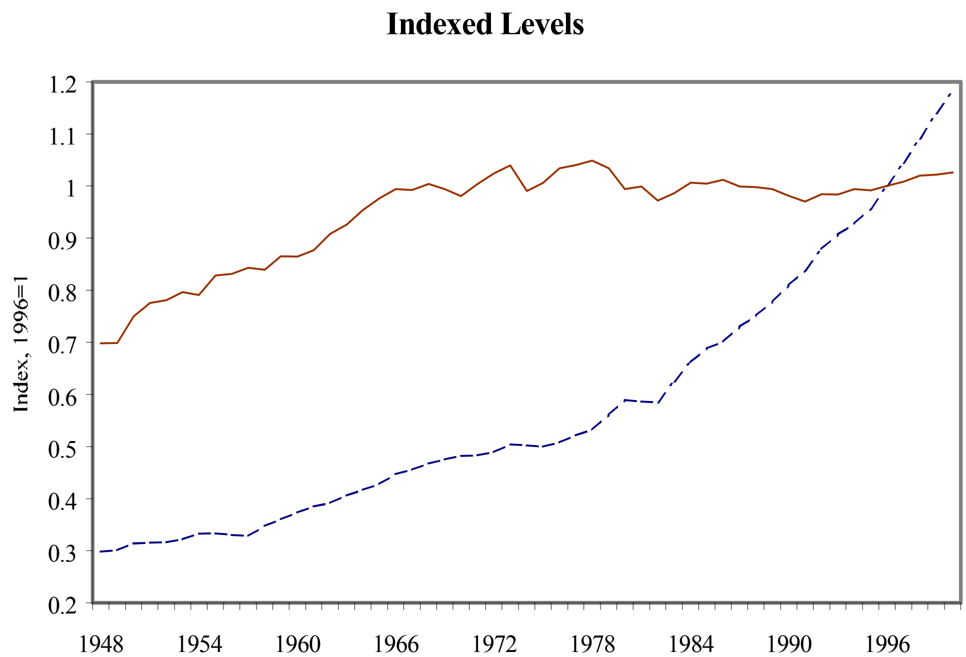


Figure 7:

Neutral and Investment-Specific Technology



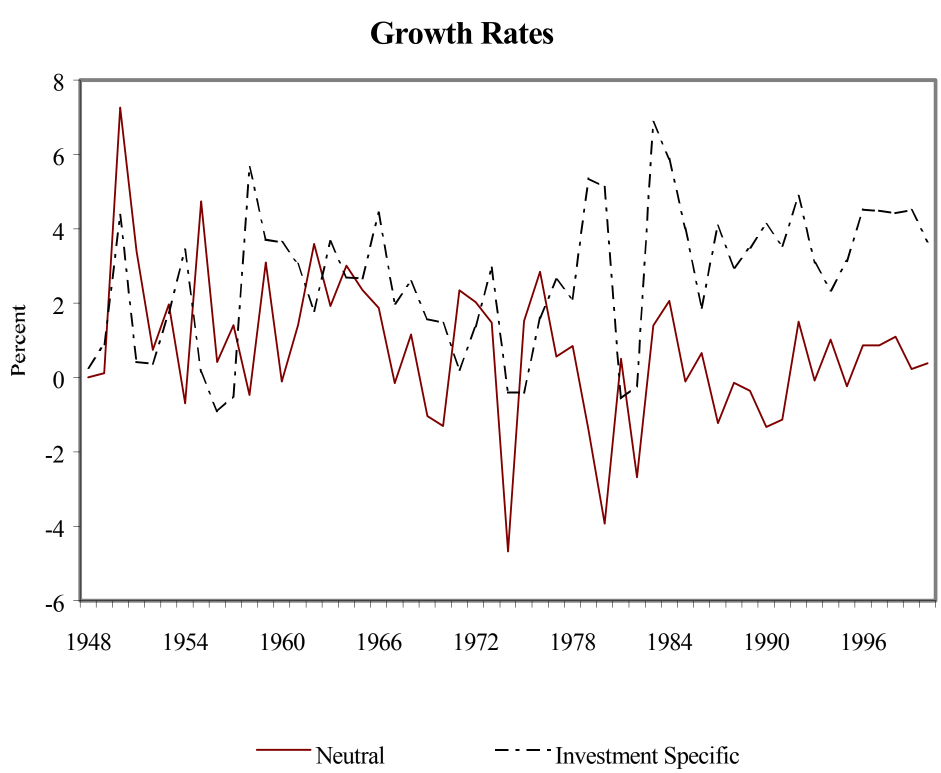


Figure 8:
Stochastic-Trends in Technology Growth

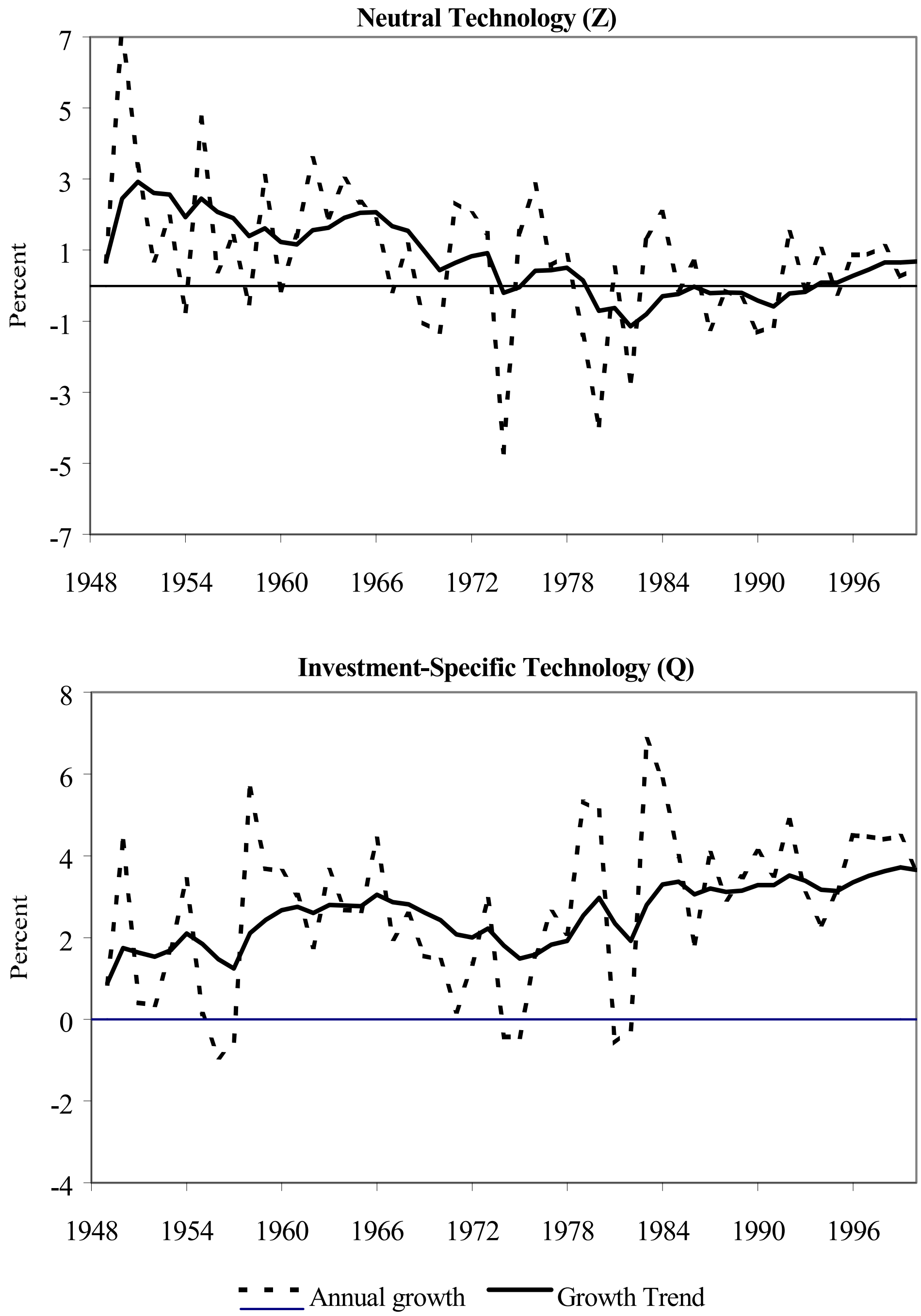


Figure 9:

Actual vs. Simulated Growth Rates -- Neutral Growth Shocks Only

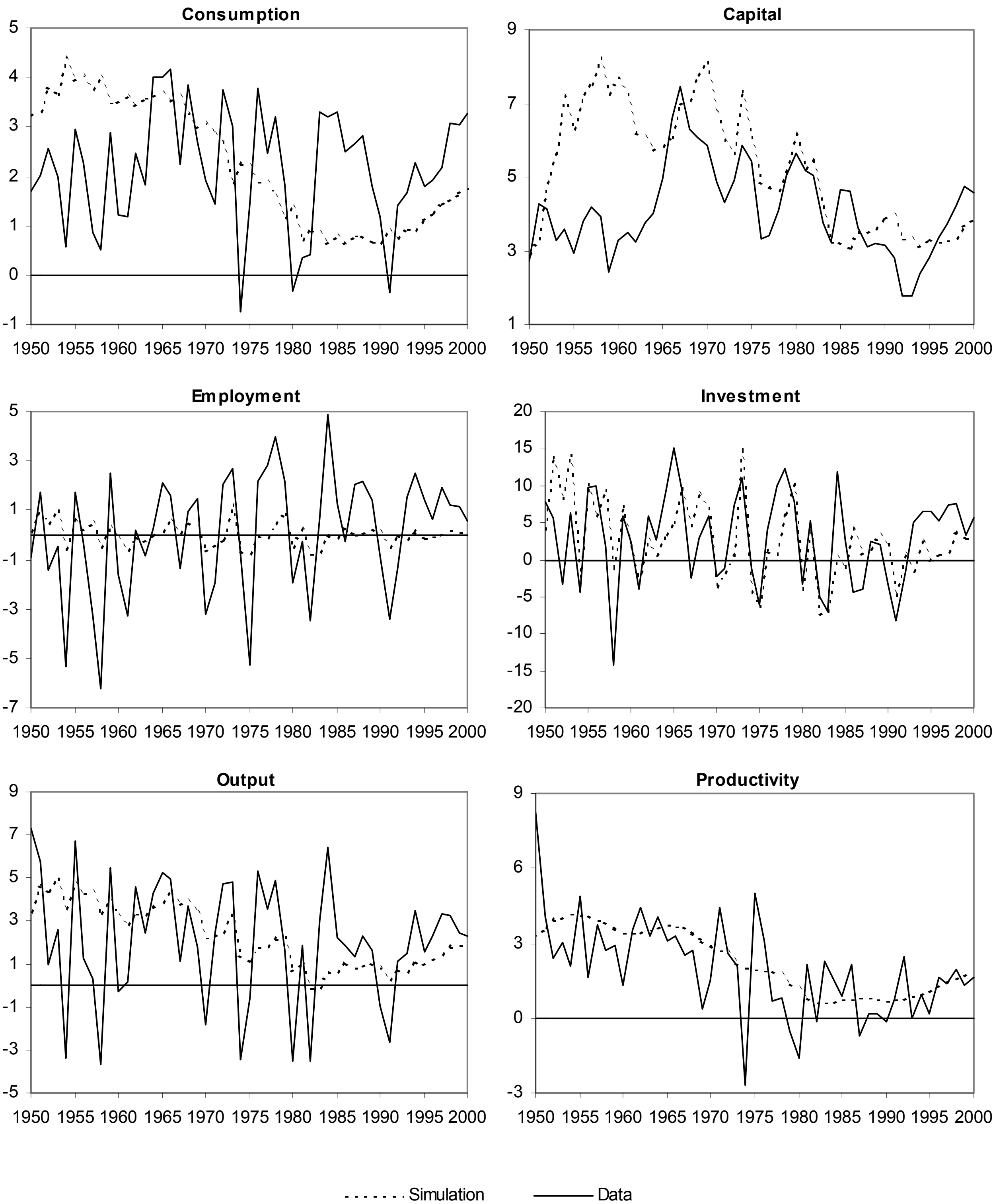


Figure 10:

Actual vs. Simulated Growth Rates -- Neutral and Investment-Specific Growth Shocks

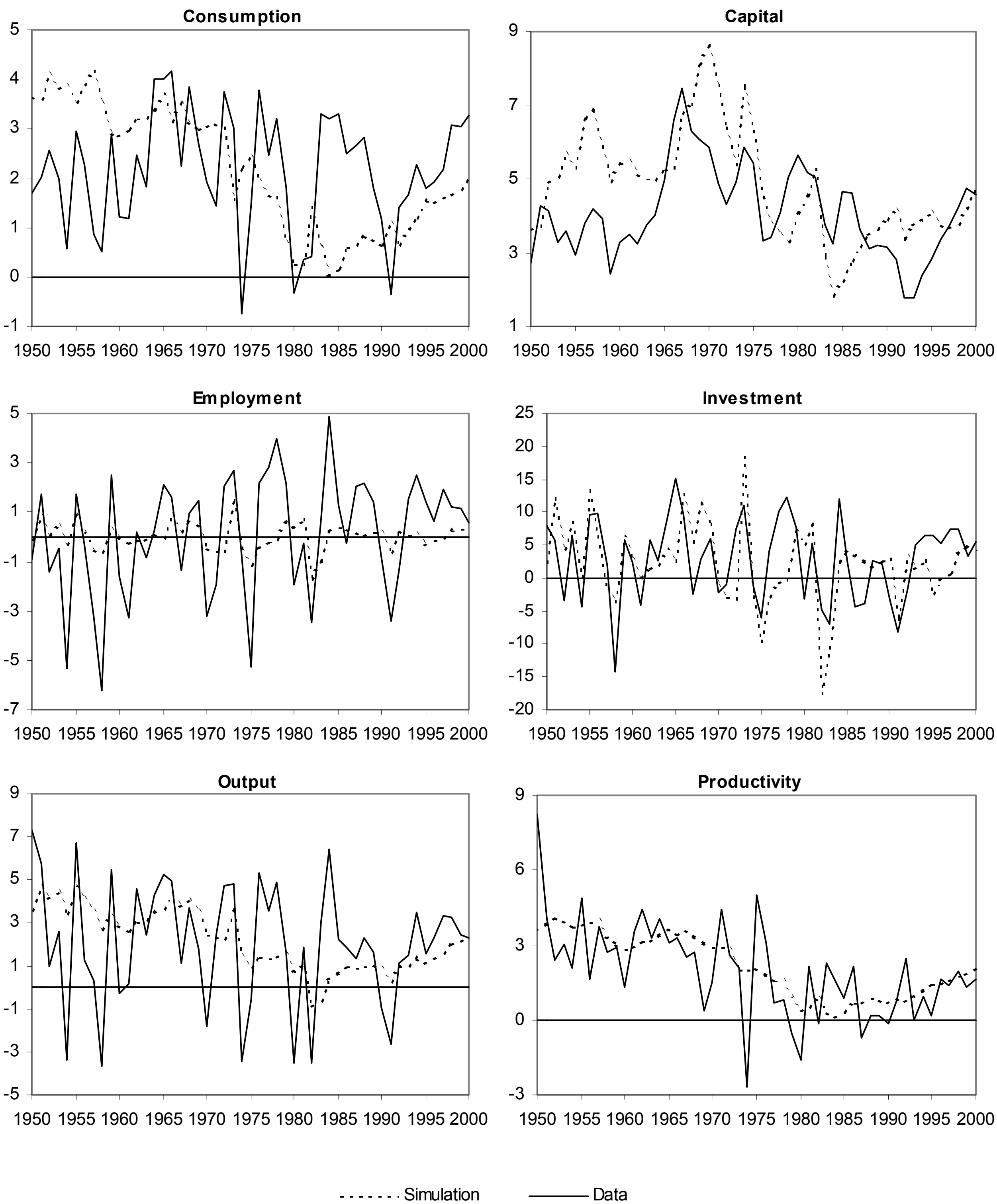


Figure 11:

Actual and Simulated Productivity Growth

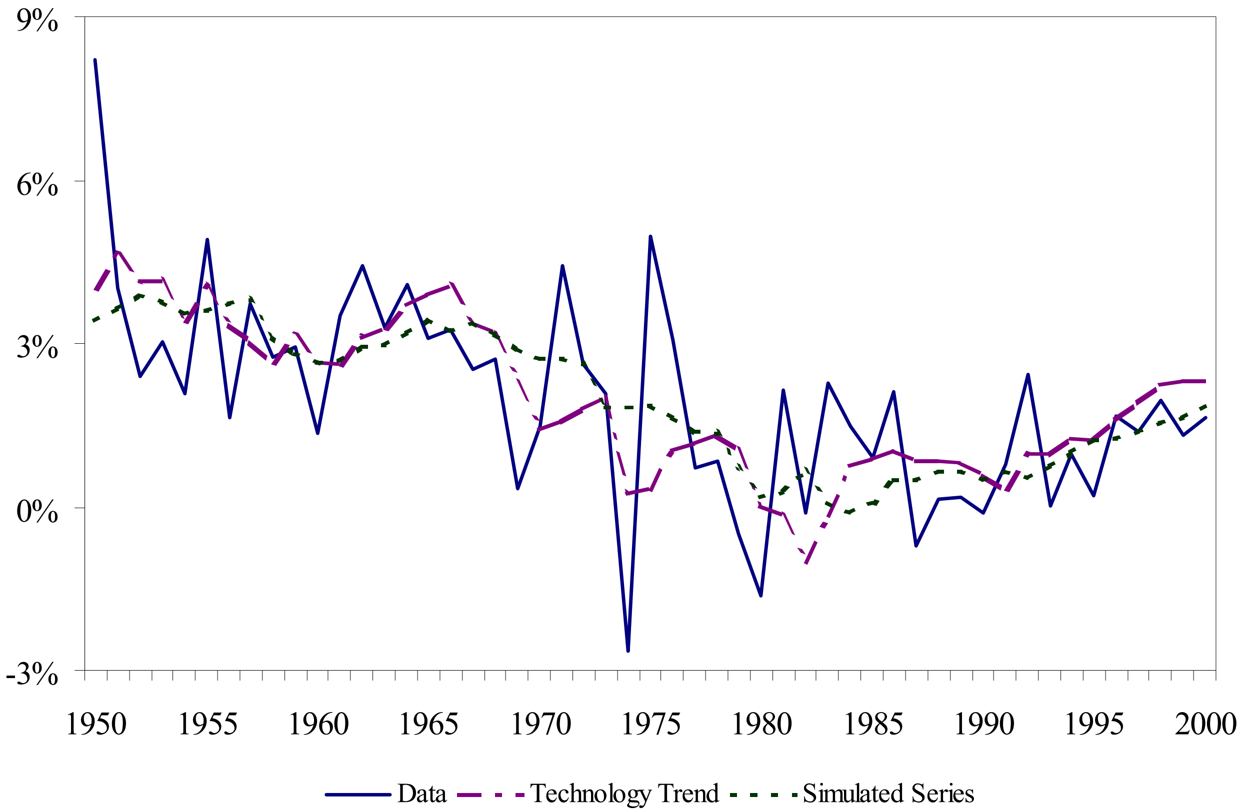


Figure 12:

Actual vs. Simulated Growth Rates -- Growth-shocks and Level-shocks