Sources of U.S. Economic Growth
in a World of Ideas

by

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July 2000

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Sources of U.S. Economic Growth in a World of Ideas

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July 5, 2000 – Version 5.0

Abstract

At least since 1950, the U.S. economy has benefited from increases in both educational attainment and research intensity. Such changes suggest, contrary to the conventional view, that the U.S. economy is far from its steady-state balanced growth path. This paper develops a model in which these facts are reconciled with the stability of average U.S. growth rates over the last century. In the model, long-run growth is driven by the worldwide discovery of new ideas, which in turn is tied to world population growth. Nevertheless, a constant growth path can temporarily be maintained at a rate greater than the long-run rate provided research intensity and educational attainment rise steadily over time. Growth accounting with this model reveals that 30 percent of U.S. growth between 1950 and 1993 is attributable to the rise in educational attainment, 50 percent is attributable to the rise in worldwide research intensity, and only about 10 to 15 percent is due to the long-run component of growth related to the increase in world population.

JEL Classification: O40, E10

An earlier version of this paper was circulated under the title “The Upcoming Slowdown in U.S. Economic Growth.” I would like to thank Paul David, Zvi Griliches, Michael Horvath, Pete Klenow, Paul Romer, Robert Solow, Steve Tadelis, John Williams, Alwyn Young, and the participants of various seminars for helpful comments. Three anonymous referees and the editor provided especially useful suggestions. Financial support from the National Science Foundation (SBR-9818911), and the Sloan Foundation is gratefully acknowledged.
1 Introduction

Over the last 125 years, the average growth rate of per capita GDP in the U.S. economy has been a steady 1.8 percent per year. Indeed, the stability of U.S. growth rates underlies the conventional view that the U.S. economy is close to its long-run steady-state balanced growth path. This view is supported by a number of stylized facts such as the absence of trends in the U.S. capital-output ratio and U.S. real interest rates, as emphasized by Kaldor (1961).

On the other hand, this conventional view is challenged by two noteworthy changes that have occurred for at least the last 50 years, and probably for much longer. First, time spent accumulating skills through formal education, which we can associate with human capital investment, has increased substantially. As of 1940, less than 25 percent of adults in the United States had completed high school, and only about 5 percent had completed four or more years of college. By 1993, more than 80 percent had completed high school, and more than 20 percent had completed at least four years of college. Second, the search for new ideas has intensified. An increasing fraction of workers in the United States and throughout the OECD consists of scientists and engineers engaged in research and development (R&D). In 1950, for example, the U.S. fraction was about 1/4 of one percent. By 1993, this fraction had risen three-fold to more than 3/4 of a percent.

In virtually any model of economic growth, these changes should lead to long-run increases in income. In neoclassical models, such changes generate transition dynamics in the short run and “level effects” in the long run. The growth rate of the economy rises temporarily and then returns to its original value, but the level of income is permanently higher as a result. In many endogenous growth models, such changes should lead to permanent increases in the growth rate itself.

As shown in Figure 1, however, the growth rate of U.S. per capita GDP
has been surprisingly stable over the last 125 years: the level of per capita GDP is well-represented by a simple time trend. Jones (1995b) used this evidence to argue against many endogenous growth models. Such models suggest that the long-run growth rate of per capita income should be rising with the increases in R&D intensity or with the increases in openness or time spent accumulating skills, but the data do not exhibit this phenomenon.

At least on the surface, the evidence also appears puzzling even from the standpoint of a neoclassical growth model. These changes should generate temporarily high growth rates and long-run level effects, but the evidence

\[\text{The data are from Maddison (1995). The growth rate from 1950 to 1994, at an annual rate of 1.95 percent, is slightly higher than the growth rate from 1870 to 1929, at 1.75 percent (see, e.g., Ben-David and Papell (1995) on this increase). At the same time, the growth rate in the 1950s and 1960s at 2.20 percent is slightly higher than the growth rate after 1970 of 1.74 percent, reflecting the well-known productivity slowdown. The main point of the figure is to show that a constant growth path fits reasonably well to a first approximation, but clearly this is only an approximation. Similar results are obtained with GDP per worker, but there is some difficulty obtaining employment data prior to 1900.}\]
in Figure 1 looks very much like an economy that is fluctuating around its balanced growth path.

How can these facts be reconciled? The explanation proposed in this paper is based on the distinction between a constant growth path and a balanced growth path. Along both paths, growth rates are constant, but the former is driven by transition dynamics while the latter is associated with a steady state. The easiest way to see how this might work is to consider a simple example. Imagine an economy described by a Solow model in which the investment rate, rather than being constant, is growing exponentially. Per capita growth in this economy could settle down to a constant rate that is higher than its long-run rate. Of course, the investment rate cannot grow forever (it is bounded at one), and when the investment rate stops growing, the growth rate of the economy will gradually decline to its long-run rate.

In the long run, the fraction of time that individuals spend accumulating skills and the share of the labor force devoted to research must level off. Over the post-war period, and most likely even before, these variables have been rising steadily. Each increase generates a transition path growth effect and a level effect on income, and the series of increases during the last 50 or 100 years have generated a constant growth path with a growth rate higher than the long-run, sustainable growth rate of the U.S. economy. This appears to be the most plausible way to reconcile the facts that motivate this paper.

A number of authors, most recently Klenow and Rodriguez-Clare (1997) and McGrattan and Schmitz (1998), have observed that while there are a large number of candidate growth models in the literature, there has been surprisingly little attention given to reconciling these models formally with data on economic growth. Progress in this direction has been made with respect to understanding differences in levels of income across countries by Mankiw, Romer and Weil (1992), Eaton and Kortum (1994), and Chari, Kehoe and McGrattan (1997), but almost no research has conducted these “quantitative theory” exercises with a focus on long-run growth. This paper
represents a first step in this direction. A formal growth model — admittedly only one of the many possible candidates — is presented and calibrated in order to understand some of the basic facts of U.S. and world economic growth.

Section 2 of the paper presents a model in which long-run growth is driven by the discovery of new ideas throughout the world. In this respect, the model builds on a large collection of previous research, including Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992) as well as earlier contributions by Phelps (1966), Shell (1966), Nordhaus (1969), and Simon (1986). In the model, growth in the world’s stock of useful knowledge is ultimately tied to growth in world research effort. While the model is constructed with an eye toward the quantitative theory exercises that follow, it also yields a number of interesting results in its own right. In particular, the model adds to a growing literature on the way in which “scale effects” matter for economic growth.

Section 3 uses the model to conduct a growth accounting exercise to document the sources of U.S. growth over the period 1950 to 1993. The results indicate that more than 80 percent of U.S. growth in these years is associated with transition dynamics, and that the long-run component of growth, driven by increases in “world” population, is less than 20 percent of the total.

If transition dynamics are so important to recent U.S. growth, why haven’t we seen the traditional signature of these dynamics, e.g. a gradual decline in growth rates? Section 4 presents the constant growth path hypothesis and reworks the growth accounting in this framework. The results from the two different accounting approaches are similar, suggesting that the constant growth path hypothesis is a reasonable approximation.

Section 5 of the paper discusses the robustness of the results, and Section 6 offers some concluding remarks.
2 Modeling Growth

Consider a world consisting of $M$ separate economies. These economies are similar in that they have the same production possibilities. They differ because of different endowments and allocations. Within an economy, all agents are identical. The economies evolve independently in all respects except one: they share ideas. Until we discuss the creation of ideas, we will focus on a representative economy and omit any subscript to distinguish economies.\(^2\)

2.1 Production Possibilities

In each economy, individuals can produce a consumption-capital good that we will call output. Total output $Y_t$ produced at time $t$ is given by

$$Y_t = A_t^\sigma K_t^\alpha H_{Yt}^{1-\alpha},$$

where $K_t$ is aggregate capital, $H_{Yt}$ is the total quantity of human capital employed to produce output, and $A_t$ is the total stock of ideas available to this economy. We assume $0 < \alpha < 1$ and $\sigma > 0$. Notice that there are constant returns to scale in $K$ and $H_Y$ holding the stock of ideas $A$ constant, and increasing returns to $K$, $H_Y$, and $A$ together. This assumption reflects the now-common notion that ideas are nonrivalrous or “infinitely expansible.”\(^3\)

We now discuss each element of this production function in turn. First, physical capital is accumulated by foregoing consumption:

$$\dot{K}_t = sK_t Y_t - dK_t, \quad K_0 > 0.$$  

\(^2\)In general, Greek letters will be used to denote parameters that are common across countries and constant over time, while Roman letters will denote variables that may differ across countries and may vary over time. The only two exceptions to this rule are the depreciation rate $d$ and the population growth rate $n$. These Roman letters will denote parameters that are constant over time and identical across countries, as described further below.

\(^3\)Quah (1996) suggests this latter term, which he attributes to a letter written by Thomas Jefferson in 1813 and discussed by David (1993). See Romer (1990) for a general discussion of this property.
The variable $s_{Kt}$ denotes the fraction of output that is invested $(1 - s_{Kt}$ is the fraction consumed), and $d > 0$ is the exogenous, constant rate of depreciation.

Next, aggregate human capital employed producing output is given by

$$H_{Yt} = h_t L_{Yt},$$  \hspace{1cm} (3)

where $h_t$ is human capital per person and $L_{Yt}$ is the total amount of raw labor employed producing output. An individual’s human capital is produced by foregoing time in the labor force. Letting $\ell_h$ represent the amount of time an individual spends accumulating human capital,

$$h_t = e^{\psi \ell_h}, \quad \psi > 0.$$  \hspace{1cm} (4)

The exponential formulation used here is the most straightforward way of incorporating human capital in a manner that is consistent with the large literature on schooling and wages following Mincer (1974) and with the substantial growth accounting literature that makes adjustments for education. It is a special case of a formulation suggested by Bils and Klenow (1996).

The final factor in the production of output is the stock of ideas, $A$. In the model, ideas represent the only link between economies; there is no trade in goods, and capital and labor are not mobile. Ideas created anywhere in the world are immediately available to be used in any economy. Therefore, the $A$ used to produce output in equation (1) corresponds to the cumulative stock of ideas created anywhere in the world and is common to all economies.\(^4\)

New ideas are produced by researchers, using a production function like that in Jones (1995a):

$$\dot{A}_t = \delta H^\lambda_{A_t} A_t^\phi, \quad A_0 > 0,$$  \hspace{1cm} (5)

\(^4\)A previous version of this paper considered a model in which the diffusion of ideas was not instantaneous and depended on economic forces. In particular, ideas produced anywhere in the world had to be learned by each person before they could be used in production. This model was more complicated but led to the same ultimate result given in equation (10) below.
where $H_A$ is effective world research effort, given by

$$H_{At} = \sum_{i=1}^{M} h_i \theta L_{Ai},$$  \hspace{1cm} (6)

In this equation, $i$ indexes the economies of this world, $L_{Ai}$ is the number of researchers in economy $i$, and $\theta \geq 0$. World research effort is the weighted sum of the number of researchers in each economy, where the weights adjust for human capital.

According to equation (5), the number of new ideas produced at any point in time depends on the number of researchers and the existing stock of ideas. Just as more workers produce more output, we assume more (efficiency-adjusted) researchers produce more new ideas. We allow $0 < \lambda \leq 1$ to capture the possibility of duplication in research: if we double the number of researchers looking for ideas at a point in time, we may less than double the number of unique discoveries. We assume $\phi < 1$, which still allows for a rich specification of the way past discoveries impact current research productivity. With $\phi > 0$, discoveries in the past raise research productivity today, reminiscent of Isaac Newton’s statement that “If I have seen farther, it is by standing on the shoulders of giants.” Alternatively, the research technology might be characterized by $\phi < 0$ if the most obvious ideas are discovered first. In this case, past discoveries make it more difficult to discover new ideas. The intermediate case of $\phi = 0$ allows these two effects to offset so that research productivity is independent of the number of ideas discovered in the past.

Finally, there is a resource constraint on labor in this economy. Each economy is populated by $N_t$ identical, infinitely-lived agents. The number of agents in each economy grows over time at the common and constant exogenous rate $n > 0$: 

$$N_t = N_0 e^{nt}, \quad N_0 > 0.$$  \hspace{1cm} (7)

\footnote{From a letter to Robert Hooke in 1675 quoted in Merton (1965).}
Each individual is endowed with one unit of time and divides this unit among producing goods, producing ideas, and producing human capital. Because time spent in school is excluded from labor force data, it is helpful to write the resource constraint as

\[ L_{At} + L_{Yt} = L_t = (1 - \ell_{ht})N_t. \]  

(8)

where \( L_t \) denotes employment. In addition, we define \( \ell_A \equiv L_A/L \) as the fraction of the labor force that works to produce ideas ("research intensity"), and \( \ell_Y \equiv L_Y/L \).

### 2.2 Allocations

It is typical in a paper like this to specify preferences and markets which, given the production possibilities of the model, determine allocations. These equilibrium conditions then provide an additional set of restrictions that can be analyzed and compared to data.

This is not the approach followed here. Instead, we take the allocations as given (ultimately, they will simply be given by the data). We will feed the allocations through the production possibilities just described to see if the “technology” of this model makes any sense. This can be viewed as a precursor to the richer analysis that comes from adding markets to the model and analyzing equilibrium conditions as well as technologies. It is reminiscent of the approach taken originally by Solow (1957) in his growth accounting exercise.

This is not to suggest that explaining the observed allocations is uninteresting. On the contrary — both problems are important, but it is fruitful to consider them one at a time. At the end of the paper, I will suggest a preliminary explanation for some of the observed allocations, but a careful analysis of this question would require another paper.

For the moment, then, we assume that \( s_K, \ell_A, \ell_h, \) and \( \ell_Y \) are given exogenously (and may differ across economies). These variables will be
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referred to as allocations.

2.3 Key Results from the Model

For the accounting exercises that follow, we need to derive several results from this basic setup. First, notice that the production function in equation (1) can be rewritten in terms of output per worker \( y_t \equiv Y_t / L_t \) as

\[
y_t = \left( \frac{K_t}{Y_t} \right)^{\frac{\alpha}{1-\alpha}} \ell_t Y_t \ h_t A_t^{\frac{\sigma}{1-\alpha}}
\]  

(9)

This expression turns out to be quite useful because along a balanced growth path, all terms on the right side except for the last are constant.

Next, if the stocks \( K \) and \( A \) grow at constant rates (which in turn requires \( H_A \) to grow at a constant rate), then this equation can be written as

\[
y_t = \left( \frac{s^* K_t}{n + g_k + d} \right)^{\frac{\alpha}{1-\alpha}} \ell_t Y_t \ e^{\psi h_t} \left( \frac{\delta}{g_A} \right)^{\frac{\lambda}{\gamma}} H_A^{\frac{\gamma}{\gamma}}
\]  

(10)

where \( k \equiv K/L \) and \( \gamma \equiv \frac{\sigma}{1-\alpha} \frac{\lambda}{1-\phi} \). Here, and in the remainder of the paper, we use the notation \( g_x \) to denote the constant growth rate of some variable \( x \) and an asterisk to denote a quantity that is growing at a constant rate.

Finally, this economy can exhibit a stable, balanced growth path, defined as a situation in which all variables grow at constant, exponential rates forever (possibly zero). It is easy to show that along such a path, the allocations must be constant. Then, from equation (10), the growth rate of output per worker is proportional to the growth rate of effective world research \( H_A \).

Finally, since \( h \) must be constant along a balanced growth path, growth in the effective number of world researchers is driven by population growth, and a balanced growth path yields

\[
g_y = \frac{\sigma}{1-\alpha} g_A = \gamma n.
\]  

(11)

2.4 Remarks

At this stage, several remarks about the model are worth noting. First, equation (11) indicates that long-run per capita growth is ultimately tied
to world population growth in this model, a result emphasized by Jones (1995a). With allocations given, a larger world population means a larger number of researchers around the world. These researchers produce more ideas, which, being infinitely expansible, raise incomes around the world. This is the intuition behind the scale effect implicit in equation (10). If the level of world population is doubled, keeping all other parameters and allocations constant, then $H^A_t$ is also doubled. This raises the level of income for all countries in the world along a balanced growth path by a factor of $2^\gamma$.

The model clarifies the level at which the scale effect associated with the nonrivalry of knowledge operates. The relevant scale variable is the population of the collection of countries that are sufficiently close to the world’s technological frontier that they can contribute to the discovery of new ideas. Neither India’s large population nor Singapore’s small population is particularly relevant to these countries’ income levels or growth rates. Rather, it is the scale of world research effort that matters for the economic performance of individual countries.

One final remark on population growth is worth mentioning. It is well-known that cross-country growth regressions typically document a negative correlation between per capita income growth and population growth. But this model appears to predict a positive relationship, as in equation (11). Can these facts be reconciled? The answer is yes. Recall that the standard negative correlation between countries is typically interpreted (e.g. as in Mankiw et al. (1992)) as reflecting the transition dynamics of the neoclassical growth model: a higher population growth rate reduces the steady-state capital-output ratio because more investment must go simply to maintain the existing capital-output ratio in the growing population. But this effect is also at work here, as indicated by the first term in parentheses in equation (10). In fact, because the $H^A_t$ term is the same across countries, this model shares exactly the neoclassical predictions for population growth in a
3 Quantitative Analysis

The model developed in the previous section provides a framework for analyzing economic growth in a particular country, recognizing that the engine of growth is the creation of ideas throughout the world. In this section, we apply this model to understand twentieth-century growth in the United States. First, however, we begin by documenting quantitatively the behavior of the key variables emphasized in the model, in particular, the stock and flow variables that appear in equations (9) and (10).

3.1 Data

Figure 2 reports data on GDP per hour worked and on the factors of production, corresponding to the quantities in equation (9). The quantities appear to grow at roughly constant rates, although a slight productivity slowdown in both output per hour and multifactor productivity is apparent. The capital-output ratio is fairly stable, as is commonly accepted, and human capital per worker rises because of the increase in educational attainment discussed below.

Turning to the allocations in equation (10), Figure 3 displays the investment share of GDP and the growth rate of aggregate hours worked in the United States. Neither of these variables displays much of a trend over the post-World War II period.

Figure 4 plots average educational attainment in the United States for persons age 25 and over, from 1950 to 1993. Educational attainment rises smoothly from a low of about 8.5 years in 1950 to a high of about 12.5 years by 1993. Ideally, one would also like to measure skills accumulated outside the formal education process, for example through on-the-job training, but...
Note: Multifactor productivity is calculated as the residual in equation (9) and corresponds to the term $A^{\frac{\sigma}{\alpha}}$. 
Figure 3: Investment Share and Growth in Hours Worked in the United States

Figure 4: Average U.S. Educational Attainment, Persons Age 25 and Over
this data doesn’t seem to be available. To map the educational attainment data into \( \ell_h \), one needs to divide by some measure of an individual’s time endowment or lifetime. Life expectancy has been rising over this period, though clearly at a much slower rate than educational attainment. On the other hand, the length of an individual’s working life has actually declined because of the decline in the age of retirement. As a rough compromise between these two trends, we will simply assume that an individual’s labor endowment has remained constant.\(^7\) Also, we will measure \( \ell_h \) directly as educational attainment and incorporate this constant term in the coefficient \( \psi \).

The last term in equation (10) is the effective number of researchers in the world. Recall from equation (6) that this number is given by a weighted sum of research labor. To provide a rough empirical measure of \( H_A \), we will make two assumptions. First, we assume that only researchers in the G-5 countries (France, West Germany, Japan, the United Kingdom, and the United States) are capable of extending the frontier of knowledge. This is motivated primarily by the lack of data for other countries prior to the 1980s and by the fact that the majority of world research effort is conducted in these countries. Second, we assume that the “quality” of these researchers is the same across the advanced countries and has remained constant over time; this can be implemented artificially by setting \( \theta = 0 \). This seems like a reasonable assumption if one thinks that to be hired in the first place, a researcher must have a certain level of education. The rise in average educational attainment, then, would not have an important effect on the quality of researchers. Under these assumptions, we can measure world \( H_A \) as the sum across the G-5 countries of the number of scientists and engineers.

\(^7\)Some rough statistics give an idea of the magnitudes involved. An individual facing a lifetime of the average cross-sectional mortality rates in 1950 would have a life expectancy at birth of 68.1 years. For 1997 the number would be 76.5 years. On the other hand, the average age of retirement for men fell from 68.7 years in 1950 to 63.7 years in 1989. The life expectancy data are taken from Table 11 in Anderson (1999). The retirement data are taken from Table 1 in Gendell and Siegel (1992).
Figure 5: Researchers and Employment in the G-5 Countries (Indexed)

![Graph showing researchers and employment in G-5 countries indexed from 1950 to 1995.]

engaged in research and development, as reported by the National Science Board (1993, 1996).

Figure 5 shows the extraordinary rise in $H_A$ since 1950. By 1993, the number of researchers had increased nearly eight-fold. This figure also illustrates another important point, which is that the rise in researchers has been much faster than the rise in the labor force. Between 1950 and 1993, the number of researchers in the G-5 rose at an average annual rate of 4.8 percent, while employment growth in the G-5 averaged only 1.2 percent per year. The implication of this difference is that research intensity — the total number of researchers divided by total employment — rose over this period. This implication is confirmed in Figure 6. Between 1950 and 1993, research intensity in the G-5 countries increased by more than a factor of four.\(^8\)

\(^8\)The lack of a smooth upward trend in U.S. research intensity is largely due to the "bulge" in research intensity between 1960 and 1975 associated with the space program and the defense buildup. Non-defense, non-space research intensity, measured by the spending share of GDP, shows a trend that is closer to monotonic. Because the direct outputs of defense and space spending are measured at cost, these sectors show, by definition, no
The magnitude of research intensity is also worth noting. In the United States and throughout the G-5 countries, less than one percent of the labor force is engaged in research according to the definition employed by the National Science Foundation. This number seems small, and the definition is surely too narrow. On the other hand, over time R&D has become a more formal activity, possibly suggesting that the measured increase overstates the true increase. Despite these possible problems, measured R&D is the only data we have, and it likely represents a reasonable benchmark provided these caveats are kept in mind.

productivity growth. For this reason, studies of R&D and productivity growth often focus on measures of R&D that exclude these categories. One can, of course, make a case for including these measures, e.g. based on things like the World Wide Web.

In the United States, the definition of R&D focuses on science and engineering. The “research” behind the creation of new consumer products like Odwalla or Jamba juice fruit drinks is not included for this reason. Also, the definition emphasizes research that requires the equivalent of a four-year college degree, meaning that the research undertaken by the young Steve Jobs, Bill Gates, and Marc Andreessen was probably excluded as well.
3.2 Accounting for U.S. Growth

We are now ready to undertake a growth accounting exercise using the model from Section 2. First, we use the form of the production function in equation (9) to decompose the growth rate of output per worker between any two points in time into its components:

\[
\hat{\gamma}_t = \frac{\alpha}{1 - \alpha} (\hat{K}_t - \hat{Y}_t) + \hat{h}_t + \hat{\ell}_t + (\frac{\sigma}{1 - \alpha} \hat{A}_t - \gamma n) + \gamma n. 
\] (12)

where a hat (\(\hat{\cdot}\)) is used to denote the average change in the log of a variable between two points in time: e.g. \(\hat{y}_t = \frac{1}{t} \log(y_t) - \log(y_0)\). By adding and subtracting the steady-state growth rate \(\gamma n\) in (12), this equation has a nice interpretation. In particular, all of the terms save the last on the right side of this equation are zero in steady state. The extent to which these terms are non-zero over any sample period reflects the importance of transition dynamics.

Several remarks concerning this approach are relevant. First, the decomposition in equation (12) is valid across any two points in time under very weak assumptions; it is not a steady-state relationship. Second, the accounting exercise is in the same spirit as classic work in growth accounting by Solow (1957), Denison (1962), and others, but it differs in some important ways. For example, multifactor productivity growth is made endogenous in this framework by specifying a complete growth model.

In addition, if the economy happens to be growing along a balanced growth path, one hundred percent of growth will be attributed to the last term in equation (12). In traditional accounting for growth in output per worker, even along a balanced growth path there will be a contribution from the capital-labor ratio. This is true even though in some sense the growth in the capital-labor ratio occurs because of total factor productivity growth. Alternatively, if one does the growth accounting in terms of capital intensity (the capital-output ratio), all of growth will be attributed to multifactor productivity growth. This exercise follows the latter approach. In this sense,
Table 1: Average Annual Growth Rates, 1950–1993

<table>
<thead>
<tr>
<th>Growth Rate of Variable</th>
<th>Sample Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output per hour $\dot{y}$</td>
<td>0.200</td>
</tr>
<tr>
<td>Capital-output ratio</td>
<td>$\dot{K} - \dot{Y}$</td>
</tr>
<tr>
<td>Share of labor in goods</td>
<td>$\dot{\ell}_Y$</td>
</tr>
<tr>
<td>Human capital</td>
<td>$\dot{h}$</td>
</tr>
<tr>
<td>Multifactor productivity</td>
<td>$\dot{A}$</td>
</tr>
<tr>
<td>R&amp;D labor</td>
<td>$\dot{H}_A$</td>
</tr>
<tr>
<td>G-5 labor force</td>
<td>$\tilde{n}$</td>
</tr>
<tr>
<td>Share of labor in R&amp;D</td>
<td>$\tilde{\ell}_A$</td>
</tr>
<tr>
<td>Annual change in $\ell_h$</td>
<td>$\Delta\ell_h$</td>
</tr>
</tbody>
</table>

Note: For data sources, see the appendix.

the exercise is closer to Solow (1956) than to Solow (1957), and follows in the tradition of David (1977), Mankiw et al. (1992), and Klenow and Rodriguez-Clare (1997).

Most of the empirical counterparts of the variables in equation (12) are readily observed. Indeed, the figures already presented contain most of the required data. The key growth rates needed for the accounting decomposition are reported in Table 1.

One element in Table 1 merits further discussion. The term $\dot{\ell}_Y$ is calculated as the growth rate of the fraction of the labor force working in producing output. Because time spent in school is not considered part of the labor force by the Bureau of Labor Statistics (BLS), $\dot{\ell}_Y$ is computed as the growth rate of $1 - \ell_A$. It shows a slight decline because of the rise in U.S. research intensity, but because less than one percent of the U.S. labor force works as a researcher, the decline is negligible.
The next step in implementing the growth accounting decomposition suggested by equation (12) is to obtain values for the parameters in that equation. We assume a value of 1/3 for the capital coefficient, $\alpha$, motivated by the usual data on capital’s share of income.

The parameter $\psi$ is readily inferred from a wealth of microeconomic evidence. Interpreting $\ell_h$ as years of schooling, the parameter $\psi$ corresponds to the return to schooling estimated by Mincer (1974) and others using log-wage regressions: output per worker, and hence the wage, differs across workers in the same economy with different amounts of schooling by the factor $\psi$. The labor market literature suggests that a reasonable value for $\psi$ is .07, which we adopt here. This value implies that an additional year of schooling has a direct effect of raising labor productivity by seven percent.

The parameters $\sigma$ and $\gamma$ are the only unknowns that remain in equation (12). Without observing ideas directly, the parameter $\sigma$ cannot be identified. We will therefore make the normalization $\sigma = 1 - \alpha$ so that $A$ is measured in units of Harrod-neutral productivity. In fact, $A$ is recovered from the data in exactly the traditional fashion: it is calculated directly from equation (9).

The parameter $\gamma$ (actually a combination of parameters, recall that $\gamma = \frac{\sigma}{1-\phi} = \frac{\lambda}{1-\phi}$) is more difficult to obtain. We proceed by estimating $\lambda$ and $\phi$ from the idea production function. More specifically, our discrete time approximating model is

$$\log B_t = \log A_t + \epsilon_t$$ \hspace{1cm} (13)

$$\Delta A_{t+1} = \delta H^\lambda_{At} A_t^\phi. \hspace{1cm} (14)$$

Abusing notation for the purposes of this estimation, we now let $B$ represent measured multifactor productivity and treat $A$ as a latent variable. In (13), $A$ is assumed to be related to multifactor productivity $B$ through i.i.d. measurement error $\epsilon$. Given data on $B_t$ and $H_{At}$, we then estimate $\delta$, $\lambda$, $\phi$, and $A_0$ using nonlinear least squares to minimize the implied sample
Table 2: Estimating $\gamma$, 1950-1993

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>4.997</td>
</tr>
<tr>
<td></td>
<td>(2.44)</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
</tr>
<tr>
<td>$\phi$</td>
<td>-16.09</td>
</tr>
<tr>
<td></td>
<td>(7.37)</td>
</tr>
<tr>
<td>$A_0$</td>
<td>4.755</td>
</tr>
<tr>
<td></td>
<td>(.085)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.980</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.292</td>
</tr>
<tr>
<td></td>
<td>(.126)</td>
</tr>
</tbody>
</table>

Note: Results from estimating the parameters in the system given in equations (13) and (14) by nonlinear least squares. Standard errors are in parentheses. In specifications (2) through (4), specific values of $\lambda$ are imposed. $\gamma$ is calculated as $\lambda/(1-\phi)$, and its standard error is computed using the delta method.

variation of the measurement error. Notice that because $\epsilon$ is mean zero and stationary, the average growth rate of $B$ and the average growth rate of $A$ over a long period will be virtually identical; hence the distinction between $A$ and $B$ is not important in the accounting exercise in equation (12).\(^{10}\)

The results of this estimation are reported in Table 2. In the first specification in which all parameters are free, one obtains an implausibly large estimate of $\lambda$ of nearly five, possibly reflecting a correlation between shocks\(^{10}\)For the estimates reported below, the average annual growth rate of the latent variable is about .0143 while average annual multifactor productivity growth rate is .0146.
Sources of U.S. Economic Growth

...to multifactor productivity and shocks to research at the business cycle frequency; the implied estimate of \( \gamma \) is 0.292. The remaining three specifications impose values of \( \lambda \) of 0.25, 0.5, and 1.0. The resulting estimates of \( \gamma \) range between 0.08 and 0.19, and the \( R^2 \) statistics indicate that there is little statistical power to distinguish between these specifications. We will consider this entire range in the accounting results below and provide an additional check later in the paper.\(^{11}\)

With these parameter values and the data from Table 1, we now turn to the growth decomposition implied by equation (12), which is reported in Table 3. Output per hour grew at an average annual rate of 2.00 percent between 1950 and 1993 in the United States. As mentioned above, the stability of the investment rate translated into a relatively stable capital-output ratio, leading to only a small but negative .07 percentage point contribution to growth. Similarly, there was a very small shift of labor away from producing goods and into producing ideas, but the composition effect associated with this change had little effect on output per hour.

The rise in educational attainment contributed 0.63 percentage points to growth in output per hour, accounting for just under 1/3 of growth during this period. Between 1950 and 1993, mean educational attainment in the United States rose by about 4 years. If each year of education leads to a seven percent rise in output per worker, increased educational attainment raised output by about 28 percent over this period, or by an annualized amount of about six-tenths of a percent per year.

The remaining 70 percent of growth is attributed to a rise in the stock of ideas produced by researchers throughout the G-5 countries. This effect is itself the sum of two pieces. First, growth in the stock of ideas in excess of the steady-state rate is the single largest contributor to growth in this

\(^{11}\)The negative estimates for \( \phi \) in Table 2 should be interpreted with care. These values are conditional on the assumption of \( \sigma = 1 - \alpha \). For smaller values of \( \sigma \), the estimated values of \( \phi \) rise in a mechanical fashion, and it is easily possible to obtain positive values of \( \phi \), e.g. if \( \sigma \) is 0.1.
Table 3: Accounting for U.S. Growth, 1950-1993

<table>
<thead>
<tr>
<th>γ</th>
<th>( \hat{y} )</th>
<th>( \frac{\alpha}{1-\alpha} (K - Y) )</th>
<th>( \hat{\ell}_Y )</th>
<th>( h )</th>
<th>( A - \gamma_n )</th>
<th>( \gamma_n )</th>
</tr>
</thead>
<tbody>
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<td>.083</td>
<td>.0200</td>
<td>-.0007</td>
<td>-.0001</td>
<td>.0063</td>
<td>.0136</td>
<td>.0010</td>
</tr>
<tr>
<td></td>
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<td>(-3.7)</td>
<td>(-0.6)</td>
<td>(31.5)</td>
<td>(67.8)</td>
<td>(5.0)</td>
</tr>
<tr>
<td>.133</td>
<td>.0200</td>
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<td>-.0001</td>
<td>.0063</td>
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<td>.0016</td>
</tr>
<tr>
<td></td>
<td>(100.0)</td>
<td>(-3.7)</td>
<td>(-0.6)</td>
<td>(31.5)</td>
<td>(64.9)</td>
<td>(8.0)</td>
</tr>
<tr>
<td>.191</td>
<td>.0200</td>
<td>-.0007</td>
<td>-.0001</td>
<td>.0063</td>
<td>.0123</td>
<td>.0023</td>
</tr>
<tr>
<td></td>
<td>(100.0)</td>
<td>(-3.7)</td>
<td>(-0.6)</td>
<td>(31.5)</td>
<td>(61.4)</td>
<td>(11.4)</td>
</tr>
<tr>
<td>.292</td>
<td>.0200</td>
<td>-.0007</td>
<td>-.0001</td>
<td>.0063</td>
<td>.0111</td>
<td>.0035</td>
</tr>
<tr>
<td></td>
<td>(100.0)</td>
<td>(-3.7)</td>
<td>(-0.6)</td>
<td>(31.5)</td>
<td>(55.3)</td>
<td>(17.5)</td>
</tr>
</tbody>
</table>

Note: This table reports the growth accounting decomposition corresponding to equation (12). The specifications are sorted according to the value for \( \gamma \) that is used (see Table 2) and correspond to values of \( \lambda \) of 0.25, 0.50, 1.0, and 4.997 respectively. Numbers in parentheses are percentages of the growth rate of output per hour.
decomposition, accounting for between 1.11 and 1.36 percentage points or 55 to 68 percent of growth, depending on the exact value of \( \gamma \). Finally, the steady-state component, associated with the general rise in G-5 employment, contributed between .10 and .35 percentage points to growth in U.S. output per hour between 1950 and 1993, accounting for only 5 to 18 percent of growth.

In this model, long-run growth arises entirely from world population growth: per capita growth requires growth in the stock of ideas which in turn requires growth in the number of researchers. Nevertheless, the decomposition in Table 3 yields the surprising result that during the period 1950 to 1993, less than 20 percent of growth was attributable to this scale effect. More than 80 percent of growth in the United States during this period is attributed to transition dynamics.

### 4 The Constant Growth Path

A natural question arises at this point. If more than 80 percent of U.S. growth in recent history is associated with transition dynamics, then why do we not see the traditional signature of a transition path, e.g., a gradual decline in growth rates to their steady state level? Why is it that U.S. growth rates over the last century or more appear so stable?

At some level, it must be that the transition dynamics associated with the various factors of production just happen to offset in such a way as to leave the growth rate of output per worker fairly constant. This could occur if the transition dynamics of the various factors take wildly different paths that, in an amazing coincidence, happen to offset. Alternatively, and perhaps more plausibly, the transition dynamics of the various factors could themselves be well-behaved in a sense that will be made precise, leading to what we will call a constant growth path.
To see this, it is convenient to rewrite equation (10) as
\[ y_t = \xi_t^{1-\alpha} \ell Y_t e^{\psi h_t} \nu \tilde{\ell}_A \tilde{L}_t. \] (15)
Several new pieces of notation are introduced in this equation. First, \( \xi_t^{1-\alpha} \equiv s_K n + g_k + d \). Second, \( \nu \equiv (\delta/g_A)^{\gamma/\lambda} \). Third, a tilde \( \tilde{\cdot} \) is used to denote a “world” aggregate (a G-5 total). Finally, we are exploiting the assumption made above about the world’s contribution to research, namely that only G-5 researchers are sufficiently close to the frontier to contribute new ideas, and that researchers have the same, unchanged skill level, which we normalize to one. Therefore, we have \( H_A = \tilde{\ell}_A \tilde{L} \), where \( \tilde{L} \) is G-5 employment and \( \tilde{\ell}_A \) is G-5 research intensity.

It is now appropriate to highlight the distinction between a constant growth path and a balanced growth path. A constant growth path (CGP) is defined as a situation in which all growth rates are constant. It is distinguished from a balanced growth path in that it is not required to be a situation that can continue forever. Notice that nothing in the derivation of equation (15) requires the allocations to be constant; we only require \( K \) and \( A \) to grow at constant rates. Based on the evidence in Figure 2, it does not seem implausible that this requirement holds, at least as a first approximation.

The consequence of this observation is that it is possible to observe a constant growth rate of \( y \) provided each of the terms in equation (15) is growing at a constant rate. More formally, taking logs and differencing equation (15) to approximate the growth rate gives
\[ g_y = \frac{\alpha}{1-\alpha} g_{\xi_k} + g_{\ell Y} + \psi \Delta h_k + \gamma g_{\tilde{\ell}_A} + \gamma \tilde{n}, \] (16)
where \( \tilde{n} \) is the growth rate of the G-5 labor force.

In steady state, every term in equation (16) except the last must be zero, so that this equation reduces back to the condition \( g_y = \gamma \tilde{n} \), familiar from equation (11). Out of steady state, however, we see that it is possible
for the growth rate of output per worker to be constant and greater than its long-run growth rate. This could occur, for example, because of growth in the human capital investment rate $\ell_h$ and in research intensity $\tilde{\ell}_A$; see Table 1 and Figures 4 and 6. Of course, this situation could not exist forever, because these shares are bounded from above at one. But, curiously, the transition dynamics could lead to a temporary, constant growth path.\(^{12}\)

Table 4 conducts the growth decomposition under the assumption of a constant growth path. Notice that in this case, all of the terms in equation (16) are observed, with the exception of $\gamma$. Instead of using the estimates of $\gamma$ obtained in the previous section, we take this opportunity to provide an independent check on our approach. That is, we calculate the value of $\gamma$ that makes equation (16) hold exactly. This calculation yields a value of 0.262, at the high end of the values obtained from the nonlinear

\(^{12}\)There is one problem with this reasoning. Because $\ell_A$, $\ell_Y$, and $\ell_h$ are related through the resource constraint, shares cannot grow simultaneously at exponential rates, meaning that a strict constant growth path is not possible. It turns out, however, that because $\ell_Y$ is close to one, this technicality is not important in practice, as we will see. An alternative would be to focus on $Y/L_Y$ instead of $Y/L$, in which case an exact CGP is possible.
least squares estimation earlier.\footnote{An alternative is to impose the values of $\gamma$ that were estimated and to include a residual in the growth decomposition. In this case, the percent contribution of the residual to growth is 43, 31, 17, and -7 for the values of $\gamma$ listed in Table 3. The CGP approximation, then, is most accurate if one believes in a value of $\lambda$ close to one, or perhaps even higher.}

The results of the CGP decomposition are roughly in line with the results obtained previously, where we did not assume a constant growth path but rather made assumptions necessary for estimating the value of $\gamma$ econometrically. Transition dynamics associated with educational attainment and the growth in research intensity account for 80 percent of growth in output per hour. The steady-state component of growth is approximately 0.3 percentage points, accounting for about 15 percent of growth. This suggests that the general findings from the accounting exercises are robust to assumptions and that the CGP interpretation of recent U.S. history is a reasonable approximation.

I have also explored the robustness of the results in Table 4 to assumptions about the mismeasurement of growth or the presence of growth due to other factors left out of the model. If the true growth rate of output per hour is higher than the measured growth rate, a larger proportion of growth is attributed to research, but the basic results are left unchanged. For example, if true growth in output per hour is actually 3 percent, transition dynamics still account for 78 percent of growth and the long-run component is 0.56 percent, accounting for 19 percent of growth. Alternatively, even if 25 percent of growth is actually due to factors outside of the model, transition dynamics associated with human capital and research intensity still account for at least 60 percent of growth. Finally, if the true growth rate of $\ell_A$ is only 1/2 of the measured growth rate, then the contribution of transitory factors remains high at 75 percent while the long-run component rises to 25 percent of recent growth. However, this increase is due to a rise in $\gamma$ to .42, which seems high when compared to the earlier econometric results, suggesting that the CGP interpretation is somewhat more strained in this
Sources of U.S. Economic Growth

The accounting exercise here begins with the year 1950 because of data limitations. Nevertheless, the available statistics related to research intensity and educational attainment suggest that this interpretation may apply for the preceding half century as well. Romer (2000) documents a steady increase in the share of engineers as a fraction of the labor force going back to 1900; a similar fact is true for chemists. According to Goldin (1999), school enrollment rates increase sharply beginning around 1900, with more modest changes over the previous fifty years.\footnote{The evidence that underlies these statements can be found in Bureau of the Census (1975). See especially the following series: D-245, D-255, and H-433.}

An implication of these results is that the growth rates experienced in the U.S. economy for the last century or so are not indicative of a steady state. The rise in research intensity and educational attainment that has occurred over this period cannot continue forever. At most the entire labor force can be devoted to producing ideas, and at most individuals can spend their entire lives accumulating human capital. When these variables stabilize, the standard pattern of transition dynamics will presumably set in, and the economy will gradually transit to its long-run rate of growth. This rate is given by \( g_y = \gamma \bar{n} \) in the model. Between 1950 and 1993, it was approximately equal to 0.3 percent in the U.S. economy, only about 15 percent of the observed growth rate.

5 Discussion

5.1 Comparison to Previous Work

A number of studies have employed traditional growth accounting methods to study the effect of R&D on growth; see, for example, Griliches (1988) and the Bureau of Labor Statistics (1989) study, as well as the references cited in these papers. Most of these studies report a fairly small accounting contribution of R&D to growth, on the order of 0.2 percentage points per
In this section, we discuss the relationship between these studies and the findings reported above.

In traditional growth accounting studies, R&D is treated as a second kind of capital investment: an R&D capital stock is constructed by cumulating past expenditures on R&D. The contribution of R&D to growth is then measured by the factor share of R&D multiplied by the growth rate of the stock of past expenditures. For example, if $Z$ is the total stock of R&D, and if human capital is ignored, the growth accounting equation under such an approach looks like

\[
\frac{\dot{Y}}{Y} = \alpha \frac{\dot{K}}{K} + (1 - \alpha) \frac{\dot{L}}{L} + \beta \frac{\dot{Z}}{Z} + \tilde{\mu},
\]

where $\tilde{\mu}$ is the growth rate of exogenous total factor productivity, and $\beta$ is the elasticity of output with respect to R&D capital. The remaining notation parallels the model presented earlier.

Since $\beta = \frac{\partial Y}{\partial Z} \frac{Z}{Y}$, this equation can be simplified to

\[
\frac{\dot{Y}}{Y} = \alpha \frac{\dot{K}}{K} + (1 - \alpha) \frac{\dot{L}}{L} + \rho \frac{R}{Y} + \tilde{\mu},
\]

where $\rho = \frac{\partial Y}{\partial Z}$ is the marginal product of R&D capital (the social return to R&D) and $R = \dot{Z}$ is the flow of R&D expenditures — net investment in R&D capital.

Assessing the impact of R&D on growth in this framework then involves measuring the social return to R&D and the net investment rate. A large number of studies have attempted to estimate these quantities, leading to a wide range of estimates. Griliches (1988) and the BLS (1989) study report social rates of return to R&D of 20 to 50 percent, or even higher; as a benchmark, the BLS chooses a value of 30 percent. The ratio of R&D expenditures to GDP in the United States is measured to be around 2 or 2.5 percent. Assuming no depreciation of R&D capital, this leads to a growth

\[\text{(17)}\]

\[\text{(18)}\]
accounting contribution of anywhere between 0.4 and 1.25 percentage points per year.

These back of the envelope calculations yield larger contributions than the results typically reported in this literature. The BLS, for example, obtains estimates in the range of 0.1 to 0.4 percentage points, with a preferred estimated of about 0.2. The difference arises primarily from two sources. First, many of these studies focus on a narrower definition of R&D that excludes federally-funded research. Second, the BLS baseline estimate assumes a depreciation rate of about 8.8 percent; the highest number in the BLS range comes when zero depreciation is assumed, as above.

To compare these contributions to the results reported in Table 3 or 4, one must make one final adjustment. The accounting in Table 3 measures productivity in Harrod-neutral units so that steady-state growth in per capita income is equal to the Harrod-neutral productivity growth rate. To convert the Hicks-neutral units given above, one divides by labor’s share of about 2/3, so that the 0.4 to 1.25 range becomes 0.6 to 1.87. Viewed this way, the contribution reported in Table 3 of 1.46 percentage points or Table 4 of 1.26 percentage points is not inconsistent with the basic growth accounting methodology used in previous studies.\textsuperscript{16} Our results are at the upper end of existing estimates, but given the uncertainties surrounding the social return to R&D and the true output share of R&D investment, they are not implausible.\textsuperscript{17}

\textsuperscript{16}The 1.46 number is multifactor productivity growth in Table 3. The 1.26 number comes from adding the contributions of research intensity and the scale effect in Table 4.

\textsuperscript{17}One can also ask what social rate of return to R&D is implied by the methodology used to get the results in Table 3 or 4. This turns out to be more complicated. In the model in this paper, the stock of ideas is not simply an R&D capital stock. An additional dollar spent on hiring a researcher yields new ideas tomorrow that increase output, but these ideas may also affect the productivity of research in the future. Jones and Williams (1998) discuss how to measure the social rate of return to R&D in a model related to this one. Applying their methods to the model in this paper, one finds that the social rate of return is not uniquely pinned down by the estimate of $\gamma$: it depends on how $\lambda$, $\phi$, and $\sigma$ combine to generate the value of $\gamma$. However, one can find seemingly plausible values of these parameters that are consistent with a social return to R&D of 30 percent.
5.2 The Future of Economic Growth

It is difficult to observe results like those in Tables 3 and 4 without wanting to inquire further about the future of economic growth. A substantial fraction of the growth experienced over at least the last half century, and perhaps before, can be attributed to factors that cannot continue forever. The long-run portion of this growth is only about 15 percent of the total. Taken at face value, this suggests that future growth may be only a small fraction of recent growth.

There are a number of considerations and qualifications that need to be taken into account in interpreting this result. First, it turns out that the U.S. economy may have experienced a similar situation earlier in its history. David (1977) notes that much of nineteenth century U.S. growth was driven by a rising investment rate in physical capital and a corresponding rise in the capital-output ratio, which building on a term used by Hicks, he calls a “grand traverse.” Historically, this particular traverse came to an end, but growth rates did not decline, as other factors took over, namely educational attainment and research intensity. A similar change could occur again.

A second consideration, also motivated by the model, relates to the production function for new ideas. The basic production function considered in this paper is \( \dot{A} = \bar{\delta}(\cdot)H_A \), where \( \bar{\delta}(\cdot) \) measures the productivity of research effort. Both because it is convenient and because it seems to fit, at least roughly, past experience, we have modeled research productivity as a simple Cobb-Douglas production function that potentially includes both research effort and the existing stock of knowledge as inputs.

It is somewhat natural to imagine that productivity in goods production is monotonically increasing: technologies get better and better over time. In this respect, the productivity of research effort may be very different. We do not know what the “universe” of ideas looks like. It could be that the discovery of past ideas makes future research more and more productive. Or this could be true, but only up to a point: the age of scientific discovery may
accelerate right up until the end, and then end. Or perhaps the universe of ideas is laid out such that there are punctuated periods of discovery followed by periods of extremely slow, gradual advance. The point is that it is difficult and perhaps impossible to know the shape of the $\delta(\cdot)$ function, and this imposes sharp limits on our ability to make statements about future growth.

Finally, consider the rise in educational attainment and research intensity. The latest grand traverse may well come to an end when the increases in these variables cease, but when will this occur? Both measures have been rising at least since 1950 and most probably since before the turn of the century. Measured research intensity is less than one percent of the labor force, so that the upper bound imposed by nature does not seem likely to bind in the near future.

6 Conclusion

This paper presents and calibrates a model of economic growth in a world of ideas. Growth in any particular country is driven in the long run by the implementation of ideas that are discovered throughout the world. In the long run, the stock of ideas is proportional to worldwide research effort, which in turn is proportional to the total population of innovating countries. In this sense, the model points out that the scale effect associated with the nonrivalry of ideas operates at a global level.

The model is employed to conduct two complementary growth accounting exercises and to understand some puzzling facts related to U.S. economic growth. While the per capita growth rate in the United States has been roughly constant on average during the last century, educational attainment and research intensity (both domestically and in the G-5 countries) have increased substantially. These facts are reconciled by highlighting the distinction between a constant growth path on the one hand and a balanced
growth path or steady state on the other. It is possible for a sequence of transition dynamics to generate growth at a constant average rate that is higher than the steady-state rate.

The accounting exercises show that U.S. growth between 1950 and 1993 can be decomposed into three key pieces. The first two pieces — associated with transition dynamics — together account for more than 80 percent of growth in output per worker. The rising level of educational attainment accounts for more than one third of growth and increased research intensity in the G-5 countries accounts for about 50 percent of growth. Only about 10 to 15 percent is due to the long-run component of growth associated with the rise in G-5 employment. While long-run growth is ultimately tied to world population growth in the model, more than 80 percent of U.S. growth in recent experience is due to other factors.

This exercise naturally raises questions about the future of U.S. and world economic growth. On the one hand, a plausible conjecture that could explain the rise in research intensity is the increased openness and development of the world economy. This explanation suggests that it is possible for the rise in research intensity to continue for some time into the future, both as the market for ideas continues to expand and as the share of the world’s population that is sufficiently skilled to push the technological frontier forward continues to rise.

Still, it is important to recognize that this situation is unsustainable. In the long run, these changes must come to an end, and when this happens, U.S. growth rates can, ceteris paribus, be expected to fall considerably.
A Data Appendix

The data used in this paper are taken from several different sources. Many of the sources are now available on-line, and the actual data series that I have used are available from the “data sets” section of http://www.stanford.edu/~chadj.

- **GDP per Hour.** Data on real GDP in chained 1996 dollars are taken from Table 2A, page 130, of Bureau of Economic Analysis (2000), available on the web at http://www.bea.doc.gov/bea/dn1.htm. Employment data are from Table B-33 of the *Economic Report of the President, 1997*. Employment is converted to total hours using the Average Weekly Hours of Production Workers (series EEU00500005) for total private industry from the Bureau of Labor Statistics and assuming a constant work year of 50 weeks. The hours data was downloaded from the “National Employment, Hours, and Earnings” link at http://www.bls.gov/top20.html. All other employment data used in this paper are in units of bodies rather than hours worked, the implicit assumption being that the hours worked are uniform across categories and countries.

- **Educational Attainment.** Average educational attainment in the population among persons 25 years old and over is calculated from Bureau of the Census (1996), Table 17 (Historical). This source reports the number of persons by “cells” of educational attainment. In computing the average, I assume that each person in a cell has the mean years of schooling for the cell (e.g. persons in the cell corresponding to one to three years of high school are assumed to have 10 years of schooling). Persons in the “four or more years of college” cell, the top cell, are assumed to have four years of college. Missing data are linearly interpolated. This data is available on-line at http://www.census.gov/population/www/socdemo/education.htm.
• **Scientists and Engineers Engaged in R&D.** The data for 1965 to 1993 are from National Science Board (1998) and National Science Board (1993). For years prior to 1965 for the U.S., data from the *Historical Statistics of the United States, Colonial Times to 1970* and various editions of the *Statistical Abstract of the United States* are used. Missing data are log-linearly interpolated. National Science Board (1998) is now available on-line at http://www.nsf.gov/sbe/srs/seind98/start.htm. For years prior to 1965 for France, Germany, Japan, and the United Kingdom, we assume that the ratio of research intensity between these countries and the United States in 1950 is the same as in 1965. Next, research intensity for intervening years is linearly interpolated for each country and then multiplied by employment (see below) to get an estimate for scientists and engineers engaged in R&D. This data is only used to construct the aggregate G-5 researchers and research intensity; it is not used on a country-by-country basis.


• *Investment.* Data on real investment in chained 1996 dollars are taken from Table 2A, page 130, of Bureau of Economic Analysis (2000), available on the web at http://www.bea.doc.gov/bea/dn1.htm. Note: unlike the capital data, the investment data does not include government investment.
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