Jobless Recoveries*

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Abstract

Historically, when an economy emerges from recession, employment grows with, or soon after, the resumption of GDP growth. However, following the two most recent recessions in the United States, employment growth has lagged the recovery in GDP by several quarters, a phenomenon that has been termed the "jobless recovery."

We explore two models that, when parameterized, easily generate economically meaningful jobless recoveries. Both models assume fluctuations are driven by technology shocks that take time to diffuse. This diffusion creates investment opportunities that decouple output and employment dynamics. The first model assumes new technology is more impactful. in some parts of the economy than others, which creates an opportunity for workers to invest in job search. In the second model, widely applicable, albeit gradually diffusing, new technology improvement creates opportunities for human capital investment that cause employment growth to lag output growth.

1 Introduction

An empirical regularity familiar to students of the business cycle is that when an economy emerges from recession, employment tends to grow either contemporaneously with, or soon after, the recovery in GDP growth. As is well-known, this historical pattern is absent in the two most recent recoveries. As Figure 1 shows, following the recessions of 1990–91 and 2000–01,

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employment continued to contract for almost two and three years, respectively. In both cases, these employment dynamics occurred in the face of very strong GDP growth, leading observers to puzzle over a phenomenon now commonly referred to as a "jobless recovery."

There are several competing conjectures about the mechanisms underlying a jobless recovery; see Schreft, Singh and Hodgson 2005, for a list. While all may turn out to be descriptive to some degree, and none completely descriptive, formal modelling and comparison to facts are needed to sort out which are the main mechanisms and which are less important. The one such exercise we know of is by Koenders and Rogerson (2005), who begin with the observation that the two most recent recessions were preceded by unusually long expansions. To the extent that "business reorganization" is costly, in the sense of diverting resources away from production for an extended period of time, the business sector is likely to postpone most restructuring activities to a period in which productivity growth slows. In this way, an unusually prolonged period of growth can result in an extended period of reorganization manifesting itself as increased job loss and/or reduced hiring.

In this paper, we offer a different perspective on the forces that might contribute to a jobless recovery. We begin with the observation that since the end of the 1981–82 recession, multifactor productivity (MFP) growth has been remarkably strong and steady, with brief slowdowns occurring in 1986, 1990, 1994 and 2000; see Figure 2. While there are well-known problems with employing measured MFP as a measure of technology, especially at higher frequencies, it is not unreasonable to interpret secular movements in MFP as reflecting an underlying process of technological development. Hence, our interpretation of the facts begins with the assumption that "technology shocks" are a primary driving force in aggregate economic activity. This assumption is shared with real-business-cycle (RBC) theory, but our view on this process is substantively different. Elsewhere, we argued that the secular movement in GDP resembles a "wave-like" pattern generated by the implementation and subsequent diffusion of general purpose technologies; see Andolfatto and MacDonald (1998). This diffusion view, which we maintain here, is similar to Schumpeter (1939), who described the process of technological development as occurring through the random arrival of technological "clusters" that diffuse slowly throughout the economy. It is also consistent with a growing body of evidence which suggests that shocks in the form of news about future productivity constitute an important source of aggregate variability.[1]

Our second key assumption is that factors of production do not adjust instantaneously in response to shocks. There are various possibilities for the cause of this gradual adjustment. We study two, one emphasizing labor-market search frictions, and another focusing on investment in human capital. In both models, a jobless recovery arises as follows. First, a technology shock leads to an upward revision in private sector forecasts of future productivity. Since the new technology diffuses gradually, the impact on productivity is muted in the early stages of the process, with GDP even declining in some circumstances as resources are diverted from production to investment in reorganization of production. As diffusion accelerates, productivity begins to rise rapidly, and reorganization activities intensify as firms capitalize on the impending productivity gains. During this intermediate stage of the process, employment may actually decline as labor is diverted toward investment (either search or human capital accumulation), and GDP rises owing to the rapid increase in productivity. This is the jobless recovery. The decoupling of GDP and employment dynamics is the key feature of our model that gives rise to the possibility of a jobless recovery.

We consider two variants of our model, both including the key assumptions described earlier, but doing so in different ways. In the first model, we assume that technological innovations vary in size and "scope", where scope means the applicability of new technology to various sectors or occupations in an economy, i.e., broad scope means applicable to most/all sectors or jobs. The idea is that technological advances typically favor some sectors of the economy more than others and that the degree to which certain sectors are impacted varies from one technology to another. The jobless recovery follows from individuals not searching in the favored sectors of the economy until diffusion makes costly search a worthwhile investment.

Our motivation for the sectoral shock model comes from Figure 3, which displays the cyclical fluctuations in the employment ratios of fifteen broadly-

[1] There is ample micro-level evidence that documents the well-known S-shaped diffusion pattern of new technologies; e.g., Griliches (1957). We think it is also reasonable to think this pattern also holds up for "general purpose technologies" (Bresnahen and Trajtenberg, 1996, and Jovanovic and Rousseau, 2003). At the macro level, Lippi and Reichlin (1994) argue that the stochastic process for GDP is more plausibly modeled as an ARIMA whose impulse-response function follows an S-shaped pattern. Further empirical support for this idea is reported in Beaudry and Portier (2004), who investigate the joint behavior of stock prices and TFP movements. These authors find that business cycles appear to be driven largely by shocks that have little impact on TFP in the short run, but a big impact on TFP in the long-run, consistent with the way we have modeled new technology.

defined sectors over the sample period 1972–2005, and offers some evidence in favor of Lilien's (1982) "sectoral shifts" hypothesis.[2] The periods during and just following the two most recent recessions both feature a significant re-ordering of employment growth rates across sectors.[3] This pattern of reorganization is less obvious in the first half of the sample, which perhaps explains why some have questioned the relevance of sectoral shifts.[4]

In our second model, new technology is applicable in all sectors of the economy, but, as before, must diffuse. Moreover, there are no search frictions, but diffusion of new technology makes investments in new (not technology specific) human capital attractive; we also allow accumulation of physical capital. Specifically, as the new technology begins to diffuse rapidly, the household sector diverts time from production towards human capital accumulation. Rapidly increasing productivity can lead to growing GDP while employment temporarily declines. This model offers an explanation for a seemingly new feature of the cyclicality of college education. That is, in the two recent recessions the college enrollment ratio continued to rise significantly after the recovery in GDP growth.

In short, in both our models, the forces generating a jobless recovery are as follows. New technology opens up the opportunity for productivity growth. Gradual diffusion of new technology causes employment reducing investments (either in search in growing sectors, or human capital) to become attractive as productivity growth accelerates, leading to employment stability or decline alongside accelerating GDP growth.

We first explore the sectoral shocks and job search model, then turn to human capital. Although not essential to our conclusion, we make the simplifying assumptions that the economy is in long run equilibrium, and is then perturbed by a single gradually-diffusing technology shock; dynamics are all a response to this one-time event. In both models, we show that "reasonable" parameterizations readily generate economically significant jobless recoveries.

[2] As many sectors display diverging secular growth patterns, we detrend the data using a Hodrick-Prescott filter (smoothing parameter equal to 100).

[3] Note also a similar (though less dramatic) episode occurring in the mid 1990s (in the middle of a strong expansion). Interestingly, there is evidence of a short "jobless expansion" occurring at about the same time; see Figure 1.

[4] In particular, see Abraham and Katz (1986), who suggest that sectoral shifts should induce a positive comovement in vacancies and unemployment, when in fact, the opposite is usually the case. We know of no model in which this claim is either formalized or corroborated.

2 Sectoral shocks and search

Time is discrete and the horizon infinite; $t = 0, 1, ...$ The economy is populated by a unit mass of infinitely-lived individuals. Individuals have identical preferences defined over stochastic consumption profiles $\{c_t \mid t \geq 0\}$. Preferences are represented by the function:

$$E_0 \sum_{t=0}^{\infty} \beta^t c_t,$$

where $0 < \beta < 1$. We will focus on perfect foresight equilibrium, so the expectations operator E_0 reflects only the presence of agent-specific uncertainty. Each individual is endowed with one unit of time, which we will assume is devoted either to working (in either production or learning) or searching.

We will be concerned with technology change that impacts various parts of the economy differentially. To model this we assume a unit continuum of firms where each firm is endowed with $k > 0$ units of a firm-specific factor of production; e.g., immobile land or capital. (Keep in mind that what we label here as a firm may in fact be better thought of as a plant or occupation; i.e., in the data, a firm may consist of several plants and/or occupations.) Since k is distributed uniformly over the unit interval, k represents both the aggregate and firm-specific quantity of the fixed factor. For simplicity, we assume that each individual owns an equal share of the economy-wide stock k.[5]

Production at every firm is described by the neoclassical production technology $y = F(k, n)$, where y denotes (homogeneous and nonstorable) output, k denotes the firm-specific factor, n denotes the level of employment, and F is linear homogeneous with diminishing marginal product in each factor (in which case $F_{kn} > 0$).

If labor were freely mobile across firms, the equilibrium wage at each date and firm would be $w^0 = F_n(k, 1)$, with the population distributed uniformly across firms. Consumption and output for each individual would be $c = y = F(k, 1)$.

[5] The only substantive role k plays in the analysis is to distribute profits. If desired, the reader can assume, as we do for the numerical analysis, that $k \equiv 1$.

2.1 Technological innovation

Suppose the allocation just described is the economy's "initial" position. Then, at some date, which we will label $t = 0$, a new technology is discovered that, if implemented, improves production possibilities at some fraction μ ($0 < \mu \leq 1$) of firms. The parameter μ indexes the *scope* of the new technology. If implemented at some firm within the scope, new technology augments the productivity of k by the factor γ ($\gamma > 1$);i.e., production possibilities at these firms become $y = F(\gamma k, n)$. The parameter γ indexes the *size* of the technological improvement. Together, scope and size will determine the economy's long-run potential GDP. Call the set of firms where production possibilities have improved *sector 1*, and the rest *sector 2*.

We think of the arrival of major new technology, e.g., microelectronics or the Internet, as occurring infrequently, and, for simplicity, model this as the arrival being completely unanticipated. Expectations along the adjustment path subsequent to the arrival of a technological breakthrough, however, are assumed fully rational. As there is no aggregate uncertainty, the equilibrium dynamics subsequent to the technology shock will follow a perfect foresight path.

Let $n(j)$ denote the level of employment at a firm located in sector j, $j = 1, 2$. If the economy could adjust instantly to the new technology, then the new equilibrium would be characterized by the following conditions (asterisks denote equilibrium values):

$$\begin{aligned}
w^* &= F_n(\gamma k, n^*(1)) \\
w^* &= F_n(k, n^*(2)) \\
1 &= \mu n^*(1) + (1-\mu) n^*(2) \\
y^* &= \mu F(\gamma k, n^*(1)) + (1-\mu) F(k, n^*(2))
\end{aligned}$$

The first two conditions describe firms' optimizing choice of labor in each sector; the others describe market clearing in the labor and goods markets respectively. Clearly, $n^*(1) > n^*(2)$, so $w^* > w^0$. That is, while employment in sector 1 expands at the expense of sector 2, since individuals are identical, equilibrium requires that they share equally in the higher wages induced by the new technology. Note that while labor productivity rises in both industries, it does so for very different reasons. In sector 1, a more efficient technology makes labor more productive. In sector 2, productivity rises because less labor increases the capital-labor ratio.

2.2 Adjustment technologies

It takes time and effort for firms to adopt major new ideas, and workers moving to more attractive jobs/occupations is not free either. To describe this process, we introduce two "adjustment technologies".

2.2.1 Technology diffusion

Following Andolfatto and MacDonald (1998), when news of new technology arrives, firms in sector 1 learn they have the *potential* to benefit, but generally must undertake costly activities to implement the new technology. That is, there is a difference between understanding the availability of a technology and learning how to implement it. Let λ_t denote the fraction of sector 1 firms that have learned how to implement the new technology. Firms in sector 1 are then labelled either *high-tech* or *low-tech* depending on whether they have implemented the new technology. For simplicity, suppose that when the new technology arrives, some (small) fraction $\lambda_0 > 0$ of firms in industry 1 learn the new technology immediately and costlessly; we will treat λ_0 as a parameter.[6]

Assume that learning to implement the new technology takes time and resources, and is not fully predictable (at the firm level). Let ι_t denote imitation effort, specifically the number of workers employed in the learning process at a representative low-tech firm (high-tech firms will devote no resources to learning). These workers must be paid a competitive wage. Given ι_t, a low-tech firm successfully learns the technology, and so can use it in subsequent periods, with probability $\xi(\iota)\lambda_t$, where $\xi(0) = 0, 0 \leq \xi < 1$ and $\xi' > 0 > \xi''$. The law of motion that describes the pattern of diffusion is then:

$$\lambda_{t+1} = \lambda_t + (1 - \lambda_t)\xi(\iota_t)\lambda_t. \tag{1}$$

Notice that the technology of learning is specified so that it becomes easier for a firm to adopt the new technology when others have already done so. The idea is that a new technology becomes progressively easier to learn the more widely it is in use because there is more commonly-known experi-

[6] The assumption that an exogenous $\lambda_0 > 0$ firms learn is merely a convenience that allows us to model the diffusion of new technology exclusively as "imitation", i.e., low tech firms learning from high tech, rather than as a blend of imitation and "innovation", the latter meaning firms can learn independently of others. If $\lambda_0 = 0$, imitation-based diffusion cannot begin. Allowing $\lambda_0 = 0$ and innovation can also be accommodated along the lines of Jovanovic and MacDonald (1994).

ence with learning how to implement the new technology. Accordingly, the diffusion of technology will follow the familiar S-shaped pattern.

2.2.2 Job search

We assume labor is perfectly mobile within a sector, but not across sectors. An individual who attempts to gain employment in a different sector *fails* to do so with probability $0 < \phi < 1$. Given failure, the individual foregoes his wage for one period. Then, the individual has the option of working in the sector in which he worked previously, or trying to switch sectors. Conditional on success, the individual immediately earns the competitive wage in his new sector.

To describe how the size of the workforce evolves in each sector, we anticipate some equilibrium behavior, viz., that no individual would choose to leave a firm within the scope of the technology shock. Thus, any firm in sector 1 will generally attract workers from outside the scope, so the workforce will typically be expanding in sector 1 and contracting in sector 2.

Let $x_t(j)$ denote the workforce (i.e., those who might work or search) *per firm* in sector j. Since we anticipate that no worker in sector 1 will search, let u_t denote the number of individuals per sector 2 firm who elect to search. Then *total* unemployment is simply $(1-\mu)u_t$, and there are $(1-\mu)u_t/\mu$ searchers per sector 1 firm. It follows that the per firm workforce within each sector evolves according to:

$$\begin{aligned} x_{t+1}(1) &= x_t(1) + (1-\phi)\left(\frac{1-\mu}{\mu}\right)u_t \\ x_{t+1}(2) &= x_t(2) - (1-\phi)u_t. \end{aligned} \tag{2}$$

Since, there is a unit mass of workers, we must have

$$\mu x_t(1) + (1-\mu)x_t(2) = 1.$$

2.3 Individual optimization and equilibrium

In this section we characterize optimal behavior for individuals and firms. Since we are modelling behavior following the arrival of the new technology, and individuals expect no further technology shocks, there is no aggregate uncertainty. Accordingly, when forming their decisions, individuals take as given a vector of deterministic sequences describing the evolution of real wages and the distribution of knowledge.

2.3.1 Firms

Let $w_t(i)$ denote the real wage in sector i at date t. We distinguish between high-tech and low-tech firms with superscripts H or L. Define:

$$\begin{aligned} \pi_t^H(1) &\equiv \max_{n_t^H(1)} \left\{ F(\gamma k, n_t^H(1)) - w_t(1) n_t^H(1) \right\} \qquad (3) \\ \pi_t^L(1) &\equiv \max_{n_t^L(1)} \left\{ F(k, n_t^L(1)) - w_t(1) n_t^L(1) \right\} \\ \pi_t(2) &\equiv \max_{n_t(2)} \{ F(k, n_t(2)) - w_t(2) n_t(2) \} \end{aligned}$$

For all firms, choosing employment devoted to production in each period coincides with optimal behavior. The only dynamic choice is faced by the low-tech firms who must also decide on the extent of effort to learn the new technology, ι_t.

Let $V_t^H(1)$ and $V_t^L(1)$ denote the capital value of optimizing high- and low-tech firms in sector 1 at date t. The sequence $\{V_t^H(1)\}_{t=0}^{\infty}$ satisfies, for all t:

$$V_t^H(1) = \pi_t^H(1) + \beta V_{t+1}^H(1), \qquad (4)$$

and the sequence $\{V_t^L(1)\}_{t=0}^{\infty}$ satisfies, for all t:

$$V_t^L(1) = \max_{\iota_t} \left\{ \begin{array}{c} \pi_t^L(1) - w_t(1)\iota_t + \\ \beta \left[(1 - \xi(\iota_t)\lambda_t) V_{t+1}^L(1) + \xi(\iota_t)\lambda_t V_{t+1}^H(1) \right] \end{array} \right\}. \qquad (5)$$

Anticipating $V_t^H(1) \geq V_t^L(1)$, the condition describing the optimal level of learning effort (assuming an interior solution) is:

$$-w_t(1) + \xi'(\iota_t)\lambda_t \beta \left[V_{t+1}^H(1) - V_{t+1}^L(1) \right] = 0. \qquad (6)$$

Optimal learning effort is increasing in the expected discounted capital gain associated with success, $\beta \left[V_{t+1}^H(1) - V_{t+1}^L(1) \right]$, and in the current state of technology absorption λ_t. Likewise, optimal learning effort decreases with the cost, $w_t(1)$, of employing workers in such an activity.

2.3.2 Workers

Let $J_t(j)$ denote the capital value associated with an individual who is employed in sector j at date t. Since individuals who work in production earn the same wage as those employed in learning activities, we need not distinguish between the two. Similarly, let Q_t denote a searcher's (necessarily from sector 2) capital value. Anticipating that $J_t(1) \geq Q_t$ and $J_t(1) \geq J_t(2)$, these capital values must satisfy:

$$\begin{aligned} J_t(1) &= w_t(1) + \beta J_{t+1}(1) \\ J_t(2) &= w_t(2) + \beta \max\{J_{t+1}(2), Q_{t+1}\} \\ Q_t &= (1-\phi)J_t(1) + \phi\beta \max\{J_{t+1}(2), Q_{t+1}\} \end{aligned} \tag{7}$$

The choice problem facing individuals in sector 2 is simple: if $J_t(2) \leq Q_t$, then search; otherwise, remain working in sector 2.

2.3.3 Equilibrium

Given our timing assumptions, the sector 1 labor market must always satisfy

$$\mu x_t(1) = \mu\left[\lambda_t n_t^H(1) + (1-\lambda_t)(n_t^L(1) + \iota_t)\right] + (1-\mu)(1-\phi)u_t. \tag{8}$$

The final term in the expression above represents the flow of individuals who successfully make a transition from sector 2 into the sector 1 labor market. At the same time, the sector 2 labor market must also obey

$$(1-\mu)x_t(2) = (1-\mu)[n_t(2) + \phi u_t]. \tag{9}$$

Of course, (8) and (9) must agree with (2.2.2).

Optimization by firms gives:

$$\begin{aligned} w_t(1) &= F_n(\gamma k, n_t^H(1)) = F_n(k, n_t^L(1)) \\ w_t(2) &= F_n(k, n_t(2)) \end{aligned}$$

in addition to condition (6).

Along the equilibrium path, unemployment will either be strictly positive or equal to zero. For strictly positive unemployment rates, individuals in sector 2 must be just indifferent between working sector 2 or searching for employment in sector 1; otherwise, working in sector 2 must dominate search. That is

$$u_t > 0 \text{ implies } J_t(2) = Q_t$$

and

$$u_t = 0 \text{ implies } J_t(2) \geq Q_t.$$

An *equilibrium* for this economy is a set of sequences:

$$\left\{x_t(1), x_t(2), u_t, \lambda_t, \iota_t, w_t(1), w_t(2), n_t^H(1), n_t^L(1), n_t(2), V_t^H(1), V_t^L(1), J_t(1), J_t(2), Q_t\right\}_{t=0}^{\infty}$$

and an initial condition $(x_0(1), x_0(2), \lambda_0)$ satisfying:

1. *Individual optimization*: given$\{w_t(1), w_t(2)\}_{t=0}^{\infty}$, the sequences $\{J_t(1), J_t(2), Q_t\}_{t=0}^{\infty}$ satisfy equation (7);
2. *Firm optimization*: given $\{w_t(1), w_t(2), \lambda_t\}_{t=0}^{\infty}$, the sequences $\{n_t^H(1), n_t^L(1), n_t(2), \iota_t, \}_{t=0}^{\infty}$ $\{V_t^H(1), V_t^L(1)\}_{t=0}^{\infty}$ satisfy equations (3), (4), (5) and (6);
3. *Labor market clearing*: (2), (2.2.2), (8) and (9) hold at every t;
4. *Search evolution*: (2.3.3) and (2.3.3) hold at every t; and
5. *Technology evolution*: (1) holds at every t.

2.4 Parameterization

We assume the following functional forms for the production and learning technologies:

$$F(\gamma^{\chi}k, n) = (\gamma^{\chi}k)^{\alpha} n^{1-\alpha}$$

and

$$\xi(\iota) = 1 - e^{-\eta\iota},$$

where $\chi = 1$ if the new technology has been implemented; $\chi = 0$ otherwise.

Taking a time interval to be one year, we assume a commonly-employed value for the discount factor, $\beta = 0.96$. We set $\alpha = 0.36$, implying a long run labor share of income equal to .64. The search failure probability is $\phi = 0.50$, so that workers who choose to switch occupations have a 50% chance of doing so successfully within one year; we explore the consequences of higher and lower values below. The parameter η governs the speed at which the new technology diffuses. Setting $\eta = 25$ implies that it takes several years for a new technology to diffuse fully; results will also be reported for different diffusion rates. Finally, we set $k = 1$.

The initial conditions are such that all firms share the same technology. Thus, when the new technology arrives, since search takes at least one period, all firms have the same initial workforce; i.e., $x_0(1) = x_0(2) = 1.0$. When the new technology arrives, we assume 1% of firms *within the scope* immediately understand how to implement it, $\lambda_0 = 0.01$.

The two remaining parameters describe size (γ) and scope (μ) of the new technology. Assuming that new technologies are eventually fully absorbed, these two parameters dictate the long-run increase in real per capita GDP. Below, we will consider different configurations of these parameters, with each configuration generating a long-run increase in real GDP equal to about 20%. In our benchmark parameterization, we set $\mu = 0.25$ and $\gamma = 3.75$.

2.5 Results

2.5.1 Benchmark parameterization

The initial situation features full employment, with sector 1 and 2 employment shares equal to .25 and .75, respectively. The initial wage rate is the same in each sectors, and equal to .64 (labor's share of initial output, which is normalized to unity).

The technology shock is narrow in scope, being (potentially) available to only 25% of firms. But for these firms, successful implementation of the new technology increases productivity by just over 60% (i.e., by a factor of $\gamma^a = 3.75^{0.36}$). On impact, however, only 1% of firms in the favorably-affected sector are able to implement the new technology immediately. Thus, the initial impact on economy-wide MFP is miniscule.

The top panel of Figure 4 displays the post-innovation time path of employment by sector, as well as unemployment. The bottom panel of Figure 4 displays the time path of wage rates and labor's share of income. At the outset, new technology does little to stimulate restructuring; unemployments remains at its normal level for two periods following the shock. Wages paid by firms within the scope, however, begin to rise almost immediately, albeit at a modest rate. The resulting "wage gap" across firms within and outside the scope eventually makes it attractive for some workers to invest in search.

The pace of restructuring begins to increase substantially four or five periods following impact. At this stage, the new technology is beginning to diffuse very quickly across firms within the scope. The rapid increase in productivity among the favorably affected firms increases their demand for labor, which continues to put upward pressure on the real wage. Workers currently located at firms outside the scope are attracted by the high wages being paid elsewhere, which is what accounts for the significant rise in unemployment. Notice that the drain of workers from firms outside the scope compels these firms to accept wage increases that are consistent with some workers continuing to work for these firms; thus, profits at these establishments decline. ("New" and "old" economy examples come to mind.)

Despite the fact that workers are able to switch occupations with moderate ease, the dynamics of this process are drawn out for several periods owing to the slow diffusion of technology. Unemployment peaks a full nine periods following the arrival of the technology shock. Eventually, the restructuring process completes its course after fourteen periods have passed. At this stage, those firms within the scope, which comprises 25% of all firms in the economy, employ over 50% of the workforce.

Figure 5 displays the time paths of GDP growth and employment growth. Notice that the arrival of the new technology initially generates a brief/mild recession (or, at least a growth slowdown). This initial decline in output occurs as some firms within the scope divert labor away from production toward learning activities. Later, output declines (despite rising productivity) as learning continues and workers from outside the scope become unemployed.

GDP growth turns positive four-five periods after the initial technology shock. At this stage, the number of firms that have learned the new technology reaches a critical mass that makes subsequent adoption much easier for laggards. As a result, the new technology begins to diffuse quickly. The rapid adoption of technology leads to a surge in productivity growth. This rapid spread of new technology makes investment in search attractive and so stimulates the pace of sectoral readjustment, and employment continues to decline even more rapidly (as unemployment peaks). During this phase of the adjustment process, the economy experiences a jobless recovery. As the new technology approaches full absorption, the rate of diffusion must necessarily slow. In the final phase of the cycle, both GDP and employment growth peak and eventually decline to their normal growth rates (zero, in this model). This is the full expansion phase of the cycle.

2.5.2 Sensitivity

In this section, we examine the sensitivity of our results to various parameter perturbations. In the first experiment, we vary the parameter that governs the ease with which workers are able to switch sectors. Figure 6 reports the results for $\phi \in \{0.0, 0.25, 0.50, 0.70\}$. Recall that ϕ measures the probability that search is *un*successful.

When $\phi = 0$, workers are able to switch occupations easily. Accordingly, there is no jobless recovery since employment remains stable as the new technology diffuses. Labor market frictions are a necessary (but not sufficient) condition for a jobless recovery. The qualitative properties of a jobless recovery appear to be robust for a wide range of parameter values. The effect of increasing the difficulty of switching sectors is to shorten the jobless recovery, while increasing the amplitude in the employment growth rate.

Now consider varying the scope of new technology, μ. Recall that μ measures the fraction of firms in the economy that may potentially benefit from the technology shock. Figure 7 reports the results for $\mu \in \{0.25, 0.50, 0.75, 0.90\}$. In each of these experiments, the size of the new technology, γ, is adjusted so that in each case the long-run GDP rises by approximately the same amount (20%). In particular, a technology shock with wider scope is smaller in size.

The top-left panel of Figure 7 records the benchmark parameterization. The effect of increasing the scope of new technology is to reduce the need for labor market restructuring. Accordingly, we see that the severity and length of the jobless recovery are reduced as the scope is widened. The increasing delay in widespread diffusion is accounted for by the fact that the size of the new technology is reduced as we increase its scope (so that the private incentive to adopt the new technology is not as great). While, the qualitative properties of a jobless recovery remain intact for a wide range of parameter values, as μ becomes large, the jobless recovery, and unemployment generally, vanishes.[7] For a technology shock to induce a significant jobless recovery, a necessary (but not sufficient) condition is that the shock is not too broad in scope.

In the final experiment, we vary the speed at which the new technology

[7] Of course, such a shock may still induce fluctuations in the aggregate labor input, as demonstrated by Andolfatto and MacDonald (1998) in the context of a model that endogenizes the labor-leisure choice. However, the point here is that a broad scope technology shock is unlikely to induce a jobless recovery.

diffuses. We do this in two ways. The first involves assuming different values for the initial fraction of firms (within the scope) who learn the new technology immediately upon its arrival, as governed by the parameter λ_0. The idea here – somewhat outside the model – is to capture the notion that for some fraction of the scope, the new technology is very similar to what is already in use. For example, an improvement in the efficiency of bioluminescence technology may be easily implemented by firms already using it, but that this will be more difficult for firms who can eventually benefit from bioluminescence, but whose current production is not based on it, e.g., manufacturers of light bulbs.

Figure 8 reports the results for $\lambda_0 \in \{0.01, 0.10, 0.25, 1.0\}$.The top-left panel of Figure 8 is the benchmark parameterization; i.e., $\lambda_0 = 0.01$. Observe how the transition dynamics are altered significantly for even a moderate increase in λ_0. For $\lambda_0 = 0.10$, the technology shock still induces a moderate recession on impact followed by a brief jobless recovery. However, when λ_0 is increased to 0.25, output remains virtually unchanged on impact, even though employment drops dramatically. In this case, the drop in employment is just compensated for by the increase in productivity. The bottom-right panel displays the limiting case where new technology is absorbed instantaneously (i.e., the standard real-business-cycle assumption). Observe that output and employment move in opposite directions only in the impact period of the shock. The subsequent transition dynamics are governed entirely by the adjustment costs in the labor market, with output and employment moving together throughout the transition period. Thus, slow technology diffusion is also a necessary (but not sufficient) condition for a technology shock to induce a jobless recovery.

The second way we vary the speed of diffusion of new technology is by assuming different values for η. An increase in η increases the probability that any given level of firm learning effort succeeds, in which case the firm implements the new technology. Figure 9 reports the results of this experiment for $\eta \in \{7.5, 10, 25, 500\}$. Interestingly, even for very high η, e.g., 500, the jobless recovery exists. The reason is that the probability of a firm successfully imitating at t is $\lambda_t \xi(\iota_t)$, approximately λ_t for large η. Thus, high η implies that imitation is very likely to be successful once the technology is widely diffused, but not before that. So if η is low, e.g., $\eta = 7.5$, making imitation difficult, this slows diffusion and prolongs the jobless recovery. But even very large values, e.g., $\eta = 500$, do not remove the jobless recovery, i.e., finite η is not necessary. As we emphasized earlier, slow diffusion is necessary. Any factor that removes this feature will also eliminate a jobless recovery in our model.

3 Human capital

In this section, we take a different approach to labor force investment in response to new technology – human capital investment.

Assume that there is a representative agent with preferences

$$\sum_{t=0}^{\infty} \beta^t u(c_t),$$

and one unit of time per period. This time can be allocated toward work (n) or education (e), where $n_t + e_t = 1$. Since there is no search, unemployment and education coincide.

The aggregate linear homogeneous production technology is:

$$y_t = z_t F(k_t, h_t n_t),$$

where z_t is technology, k_t is physical capital, and h_t is human capital. Physical capital evolves according to:

$$k_{t+1} = (1 - \delta_k)k_t + y_t - c_t.$$

Human capital evolves according to:

$$h_{t+1} = (1 - \delta_h)h_t + \phi(e_t),$$

where ϕ is an increasing and concave function.

The economy begins in a steady-state with technology level z_L. An unanticipated technology shock (information) reveals a new potential level of technology given by $z_H > z_L$. This new technology diffuses slowly according to an exogenous process. Let λ_t denote the fraction of the new technology that is absorbed as of date t. Assume that:

$$\lambda_{t+1} = \lambda_t + \eta(1 - \lambda_t)\lambda_t,$$

with λ_0 (small) given; and where $\eta > 0$ is a parameter governing the speed of diffusion. Thus, the level of technology at any date t (subsequent to the arrival of the shock) is given by $z_t = (1 - \lambda_t)z_L + \lambda_t z_H$.

In recursive form, the planner's problem can be stated as follows:

$$v_t(k,h) = \max_{e,k'} \left\{ u\left(z_t F(k, h(1-e)) + (1-\delta_k)k - k'\right) + \beta v_{t+1}(k', (1-\delta_h)h + \phi(e)) \right\}$$

The first order conditions are given by:

$$h z_t F_2(k, h(1-e)) u'(c_t) = \phi'(e)\beta \frac{dv_{t+1}}{dh'}$$

$$u'(c_t) = \left[1 + z_{t+1}F_1(k', \phi(e)(1-e')) - \delta_k\right] u'(c_{t+1}),$$

where $c_t = z_t F(k, h(1-e)) + (1-\delta_k)k - k'$.

From the envelope theorem,

$$\begin{aligned} \frac{dv_t}{dh} &= (1-e)z_t F_2(k, h(1-e))u'(c_t) + (1-\delta_h)\beta \frac{dv_{t+1}}{dh'}, \text{ and} \\ \frac{dv_{t+1}}{dh'} &= (1-e')z_{t+1}F_2(k', \phi(e)(1-e'))u'(c_{t+1}). \end{aligned}$$

Collecting all the relevant restrictions, and letting $\varphi_t \equiv \frac{dv_t}{dh}$, we have:

$$\begin{aligned} h_t z_t F_2(k_t, h_t(1-e_t))u'(c_t) &= \phi'(e_t)\beta(1-e_{t+1})z_{t+1}F_2(k_{t+1}, h_{t+1}(1-e_{t+1}))u'(c_{t+1}); \\ u'(c_t) &= [1 + z_{t+1}F_1(k_{t+1}, h_{t+1}(1-e_{t+1})) - \delta_k]\, \beta u'(c_{t+1}); \\ \varphi_t &= (1-e_t)z_t F_2(k_t, h_t(1-e_t))u'(c_t) + (1-\delta_h)\beta\varphi_{t+1}; \\ c_t &= z_t F(k_t, h_t(1-e_t)) + (1-\delta_k)k_t - k_{t+1}; \\ h_{t+1} &= (1-\delta_h)h_t + \phi(e_t); \end{aligned}$$

with k_0, h_0, z_0 given. These five restrictions can be used to compute the economy's dynamic response $\{c_t, e_t, \varphi_t, k_{t+1}, h_{t+1}\}$ to the technology shock $\{z_t\}$, assuming that the initial physical and human capital stocks (k_0, h_0) are the steady-state levels associated with the initial technology level $z_0 = z_L$.

3.1 Parameterization and Results

In our numerical example, we use the functional forms: $u(x) = \ln(x)$, $F(x,y) = x^\theta y^{1-\theta}$, and $\phi(x) = x^\alpha$. The parameterization is as follows:

θ	α	δ_k	δ_h	z_L	z_H	λ_0	β	η
0.35	0.75	0.10	0.25	10	12	0.01	0.96	0.75

The model's impulse-response dynamics are displayed in Figure 10.

The top panel of Figure 10 records the growth rates for human capital investment and the expenditure components of GDP following the (unexpected) news of a new technology that will eventually lead to a 20% in MFP. On impact, the news results in a slight boom in consumption and a sharp drop in capital spending; this behavior reflects a positive wealth effect. Further along, consumption remains relatively stable while capital spending continues to decline and the economy enters into a mild recession. Investment in human capital grows throughout the recession, in anticipation of the future boom. As technology begins to diffuse rapidly, capital spending rebounds and the acquisition of human capital continues to grow. As the acquisition of human capital diverts time away from production, employment continues to contract. The bottom panel of Figure 10 reveals that this phase is associated with a jobless recovery.

Our first model emphasized workers investing by searching for the new job opportunities created by technology improvement that impacts firms unevenly. The second model stresses human investments based on opportunity created by widely applicable new technology. Figure 11 reproduces the employment/population data from Figure 1 for comparison to the college enrollment ratio (**David: Need a clear definition here**). Interestingly, alongside both jobless recoveries ('91-'93 and '01-'04), the college enrollment ratio attained historic highs, peaking in '92 and '04. The notion that college enrollment has a countercyclical component is familiar to all who work in education. However, that it enrollment growth persists significantly after employment opportunities have begun to improve is a new feature, and as our model shows, possibly related to the same forces driving jobless recoveries.

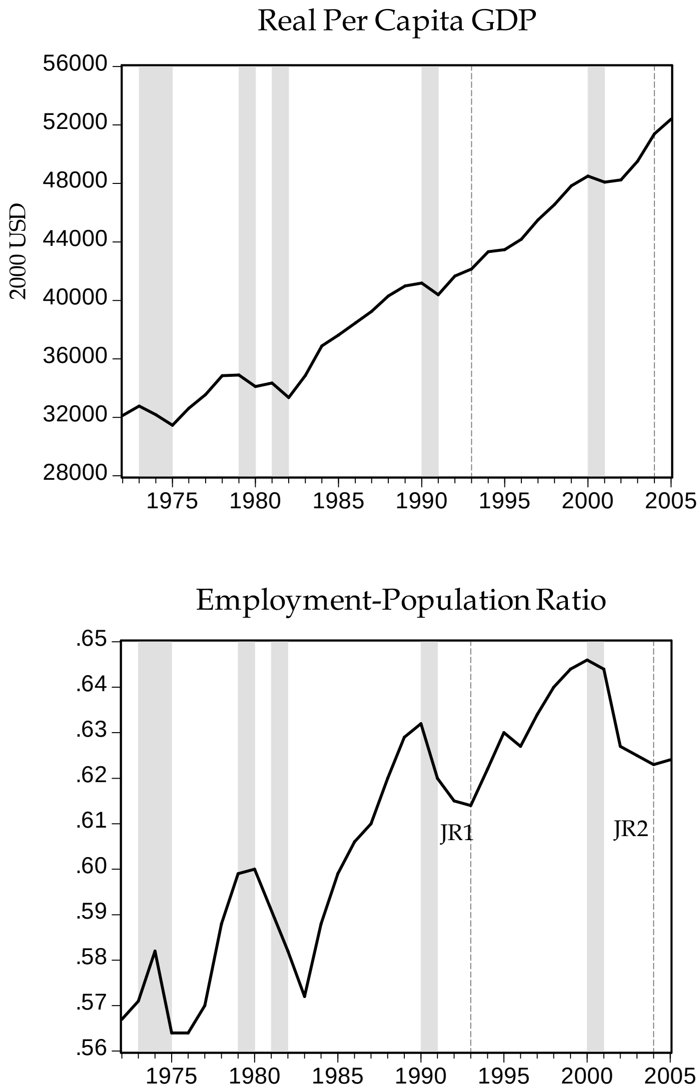
4 Summary

It is an empirical fact that the pattern of economic development in advanced economies is characterized by growth and fluctuations in GDP. The role of technological advance in generating growth is widely accepted. Real business cycle (RBC) theory asserts that since there is no *a priori* reason to expect the process of discovery to occur evenly over time, technology shocks may be largely responsible for both growth and fluctuations. In standard RBC environments, however, positive technological developments do not lead to recessions or jobless recoveries.

In this paper we explored the properties of an RBC model in which growth is driven by technological advances that improve factor productivity, that vary in the degree to which they affect the structure of the economy, that do not diffuse instantaneously, and that generate lasting labor market adjustments. The combination of technology advance with limited scope, less than instantaneous diffusion, and job search, yields income and employment dynamics that easily display recessions and jobless recoveries that are both quantitatively important and, in a general way, similar to the jobless recoveries whose emergence has proved so puzzling to many observers of aggregate economic activity. The combination of slow diffusion of new technology and human capital investment has the same impact.

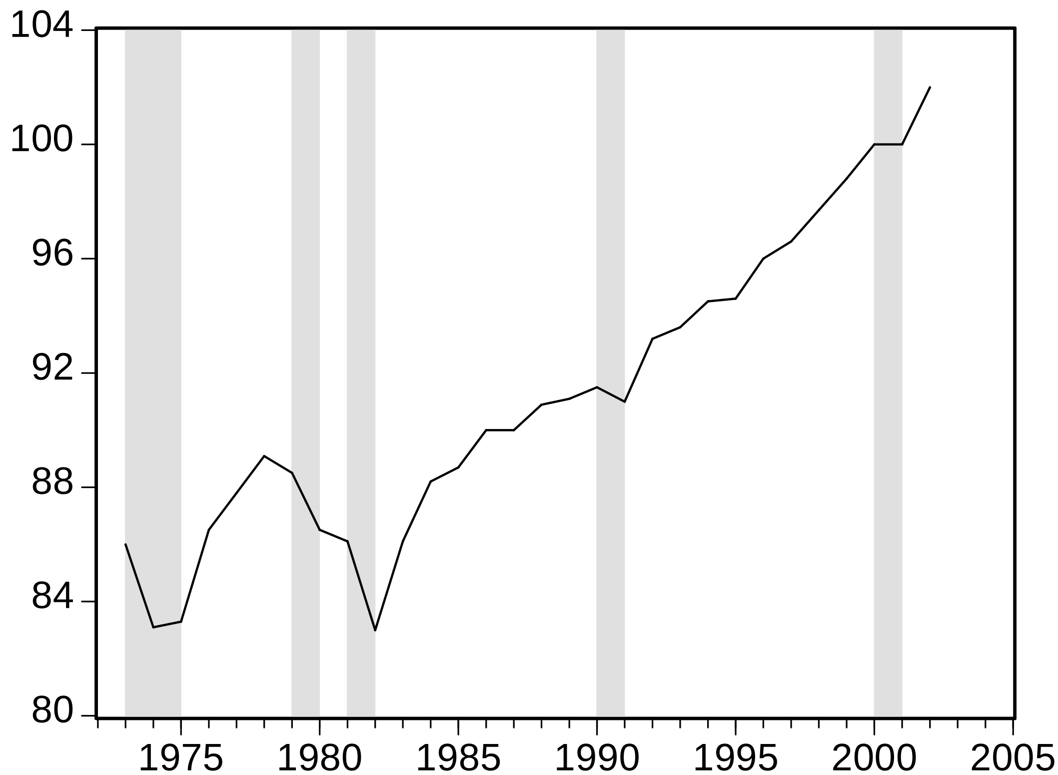
Our search and sectoral shock model is the more novel of the two we explore in this paper. And it raises some intriguing new questions. For example, what factors determine the attributes of technological developments in terms of their size, scope, and ease of implementation? According to our scope-based explanation of recently observed dynamics, new technology is systematically narrower in scope but greater in magnitude. Is this reflective of some underlying change in economic fundamentals, or is it serendipitous?

FIGURE 1
U.S. Output and Employment



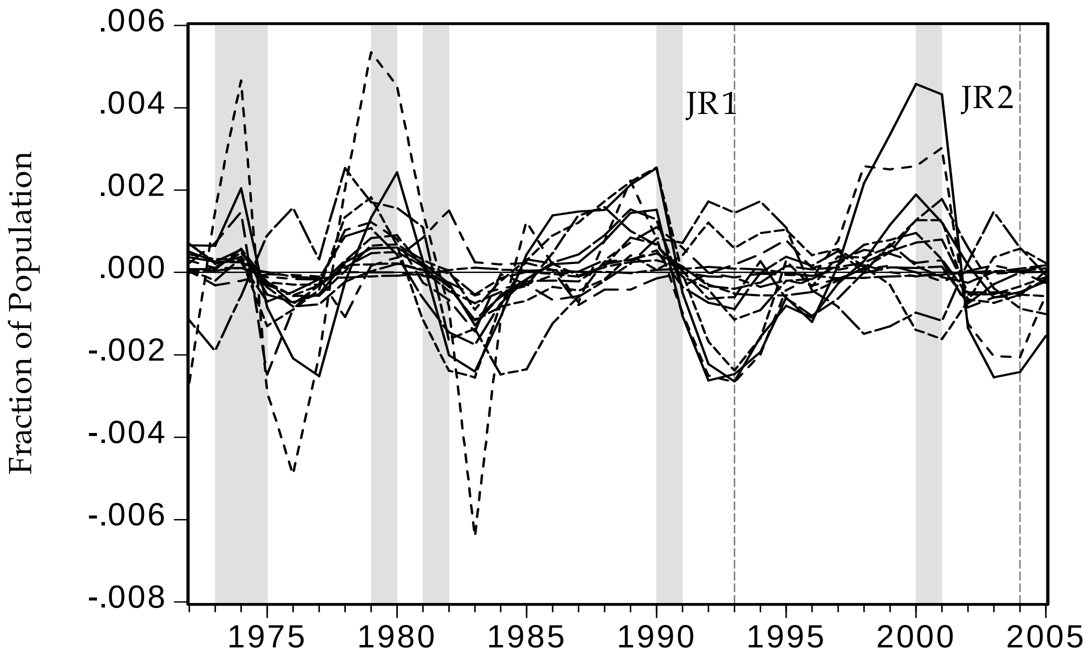
Sources: Real GDP, U.S. Department of Commerce: BEA, Series ID: GDPCA;
Employment, U.S. Department of Labor: BLS, Series ID: LNS12000000;
Population, U.S. Department of Commerce: BEA Series ID: POPTHM.

FIGURE 2
U.S. Multifactor Productivity (Index, 2000 = 100)



Source: BLS Series ID MPU750023 (Private Nonfarm Business)

FIGURE 3
Sectoral Employment Ratios
Cyclical Deviations from HP Trend



Sectors: Natural Resources and Mining; Construction; Manufacturing (Durable); Manufacturing (Nondurable); Wholesale Trade; Retail Trade; Transportation and Warehousing; Utilities; Information; Financial; Professional; Education and Health; Leisure; Other Services; Government.
Source: BLS (January of each year).

FIGURE 4
Employment, Wage, and Cost Dynamics
Following a Technology Shock

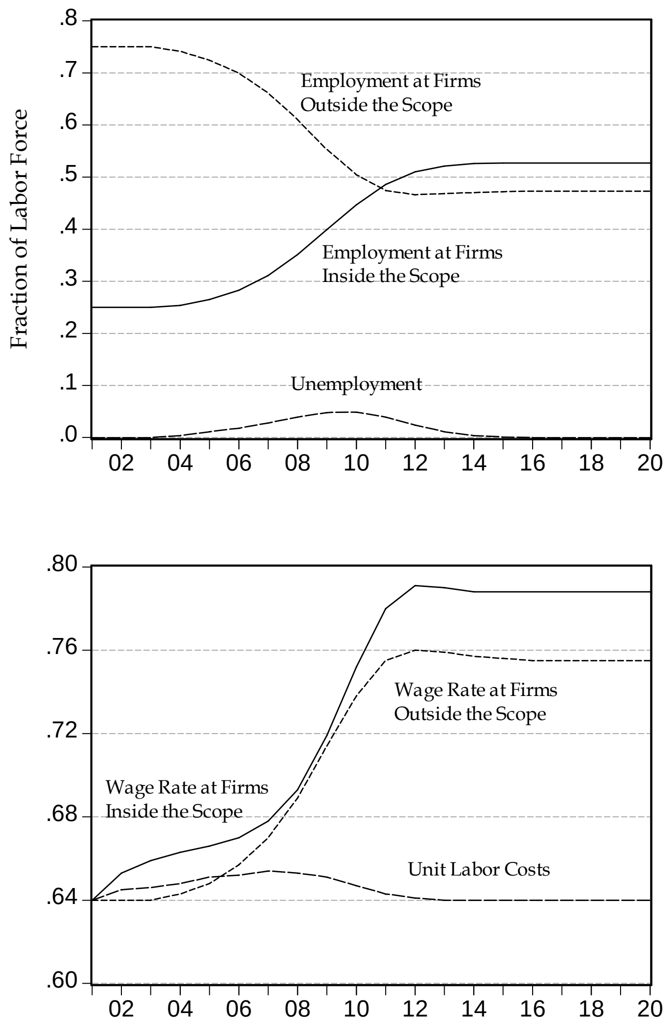


FIGURE 5
GDP and Employment Growth Rate Dynamics
Following a Sectoral Technology Shock

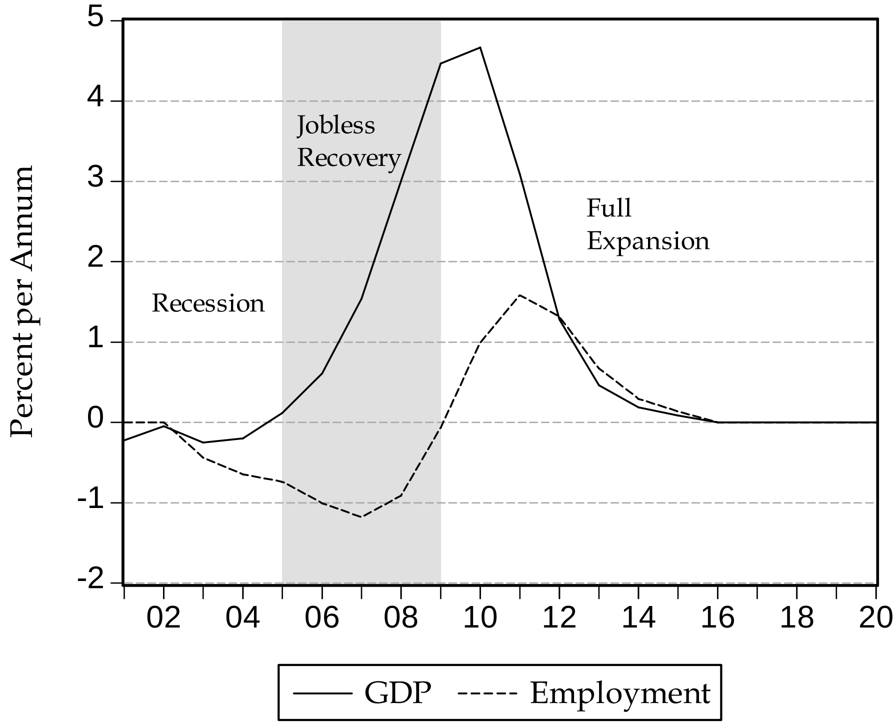


FIGURE 6
GDP and Employment Growth Dynamics
Following a Technology Shock for
Different Job Finding Rates

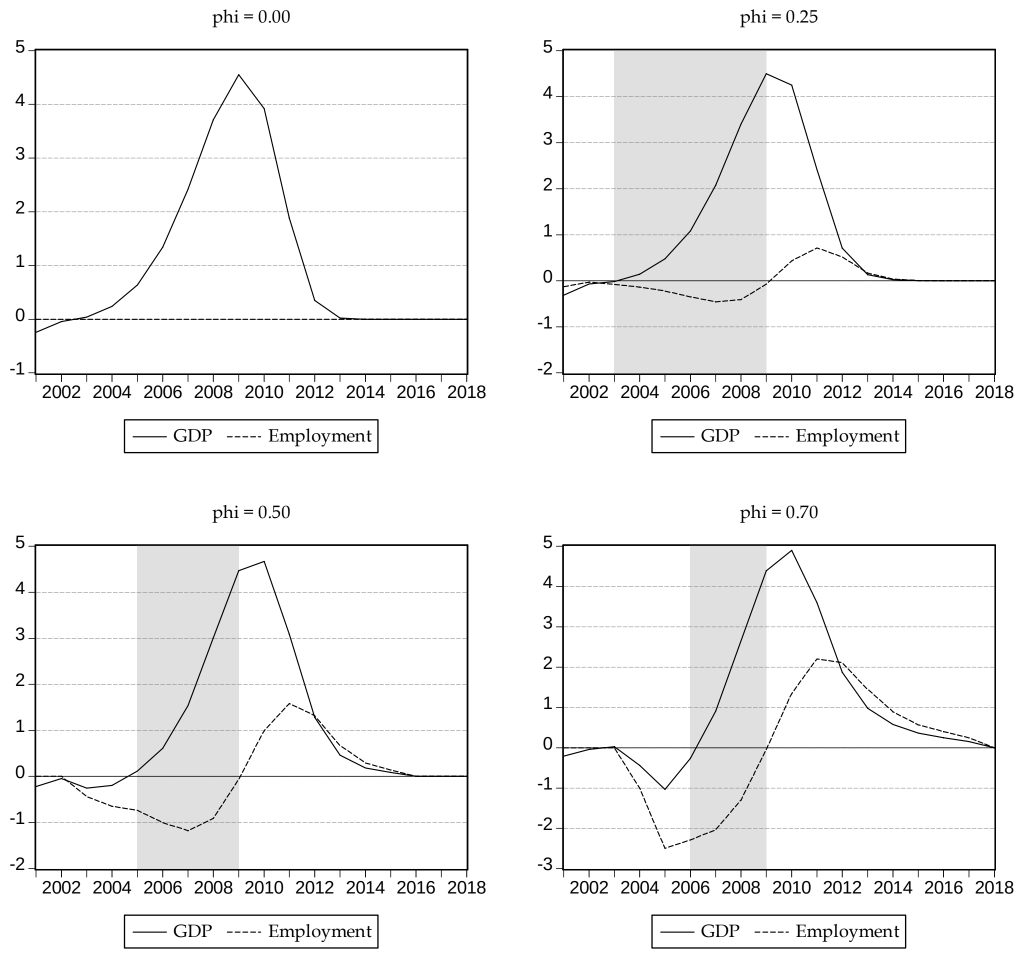


FIGURE 7
GDP and Employment Dynamics
Following a Technology Shock
of Varying Scope

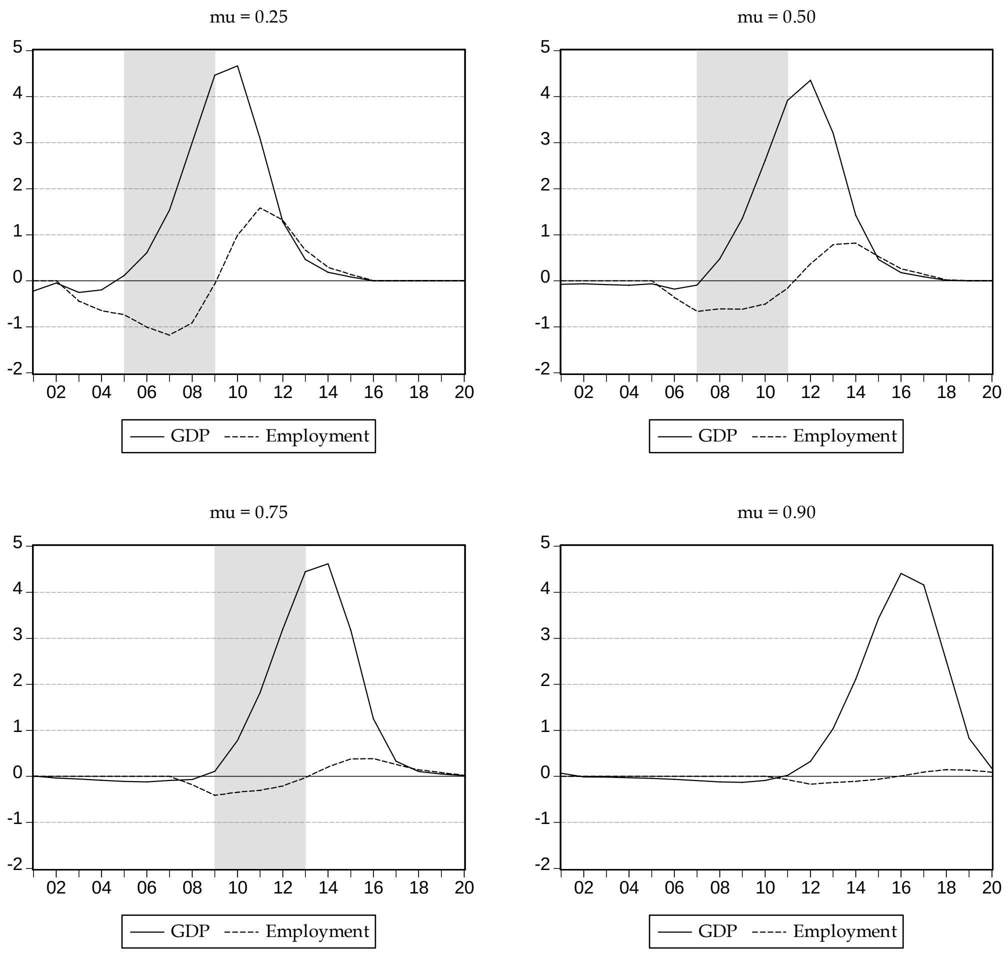


FIGURE 8
GDP and Employment Dynamics
Following a Technology Shock
for Various Diffusion Rates

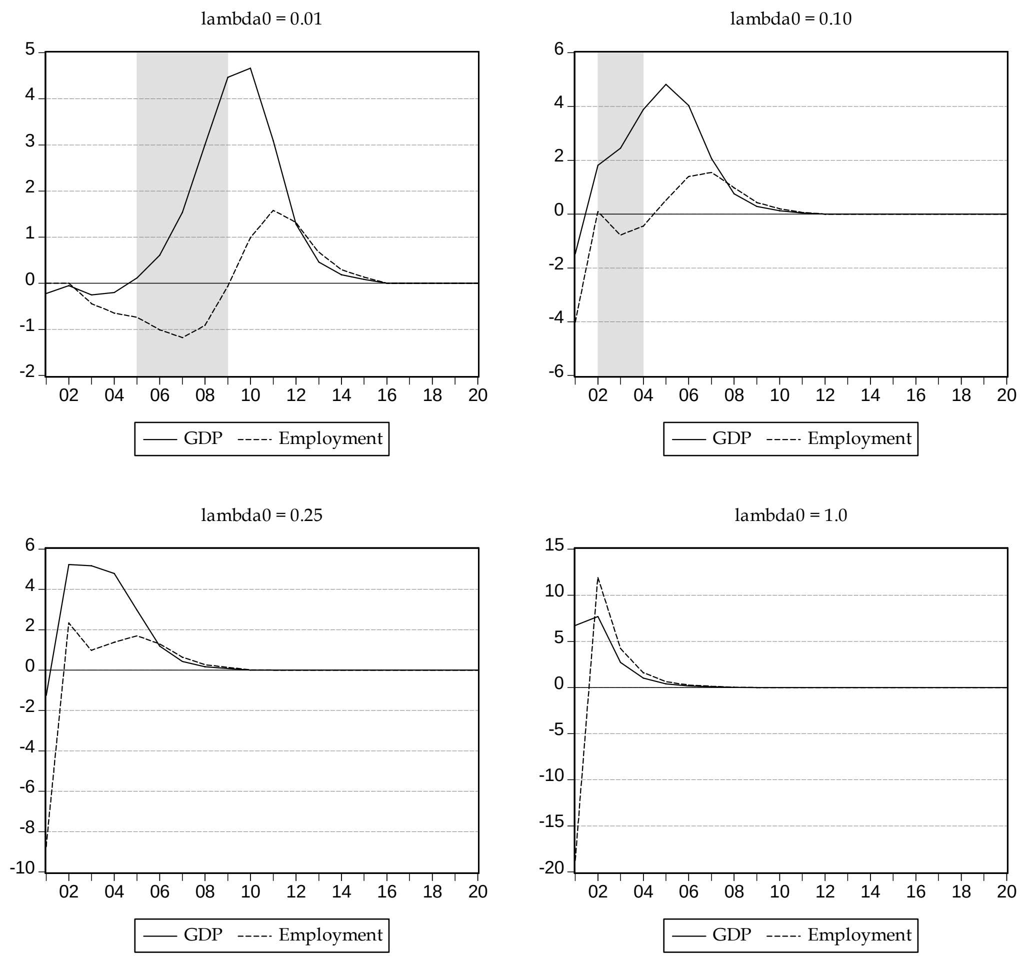


FIGURE 9
GDP and Employment Growth Dynamics
Following a Technology Shock as the
Ease of Imitation Varies

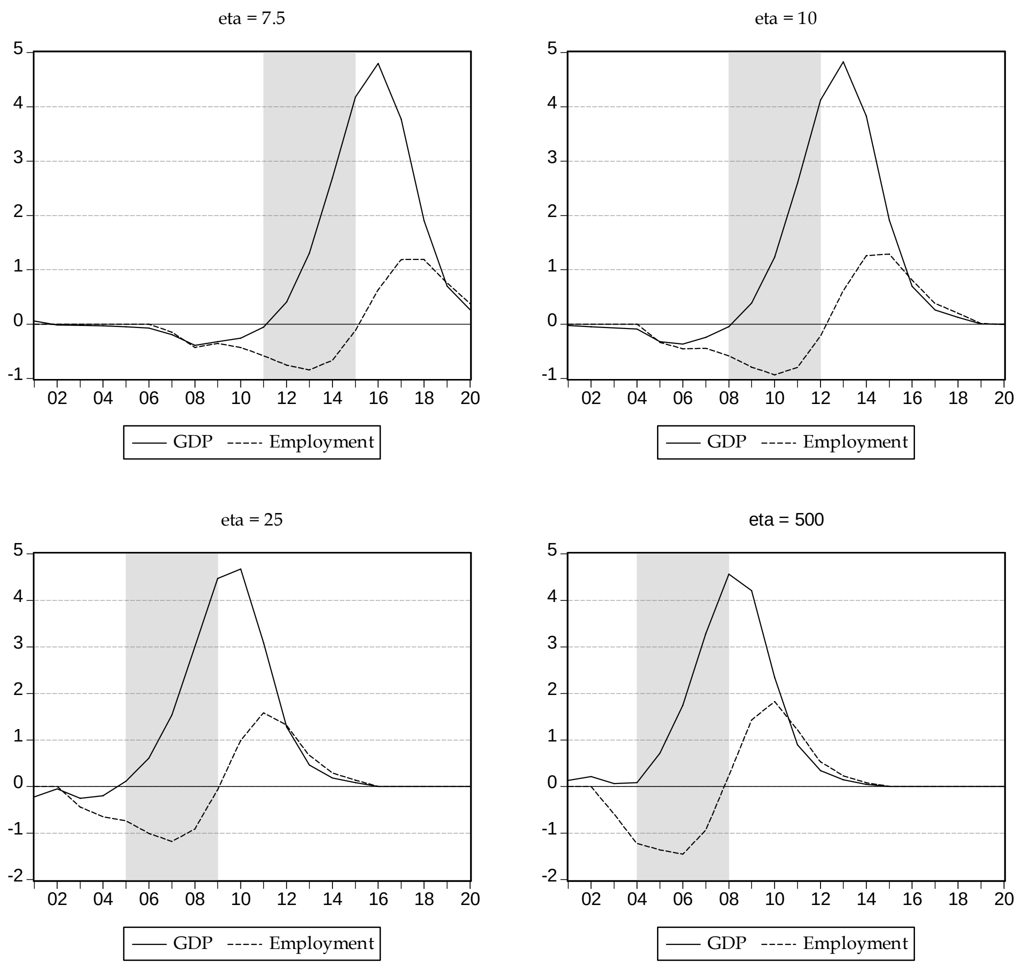


FIGURE 10
Dynamic Response to a Technology Shock
(Human Capital Model)

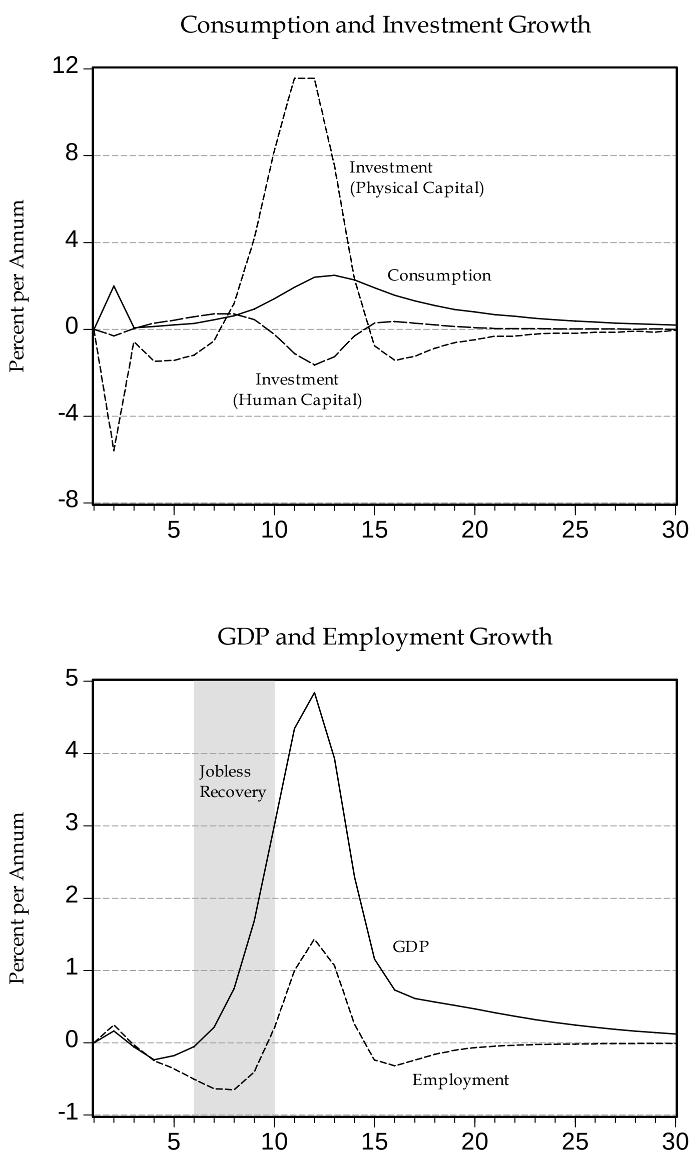
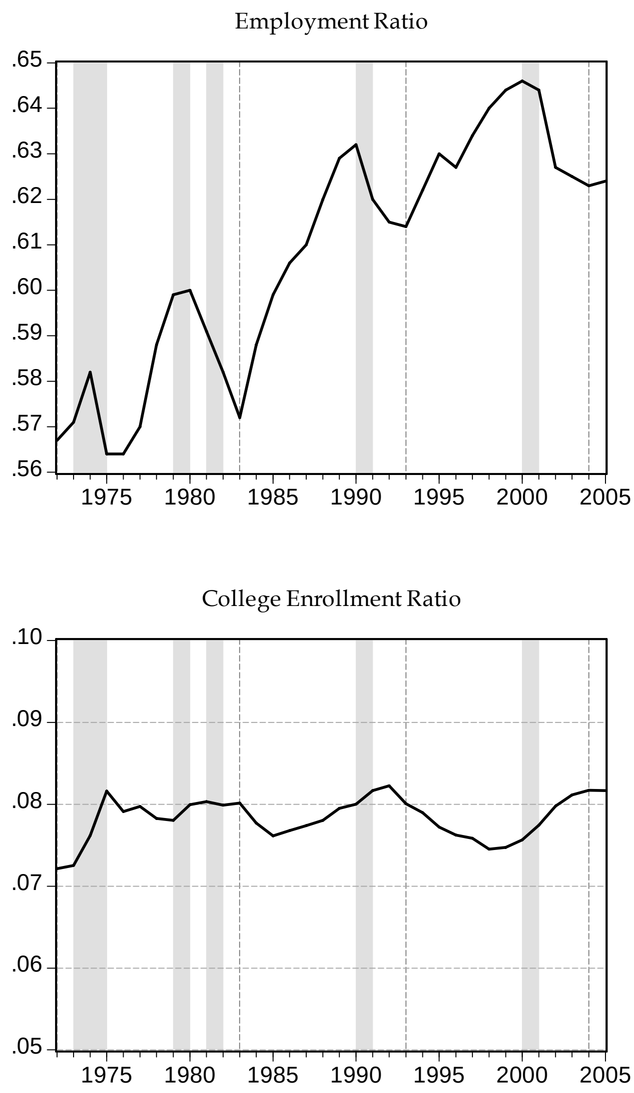


FIGURE 11
U.S. Employment and College Enrollment



Source: U.S. Department of Education, NCES
http://www.nces.ed.gov/programs/digest/d04/tables/dt04_003.asp

5 References

1. Andolfatto, David and Glenn M. MacDonald (1998). "Technology Diffusion and Aggregate Dynamics," *Review of Economic Dynamics*, April, 1(2): 338-370.

2. Bernanke, Ben S. (2003). "The Jobless Recovery," www.federalreserve.gov/ boarddocs/ speeches/ 2003/ 200311062/ default.htm

3. Bernstein, Jared (2003). "The Jobless Recovery," www.epinet.org/ content.cfm/ issuebriefs_ib186

4. Beaudry, Paul and Franck Portier (2004). "Stock Prices, News, and Economic Fluctuations," Manuscript: University of British Columbia.

5. Bils, Mark and Peter J. Klenow (2002). "Some Evidence on the Importance of Sticky Prices," Manuscript: Federal Reserve Bank of Minneapolis.

6. Bresnahen, T. F. and M. Trajtenberg (1996). "General Purpose Technologies: Engines of Growth?" *Journal of Econometrics*, Annals of Econometrics, 65: 83–108.

7. Greenwood, Jeremy, Glenn MacDonald and Guang Zhang (1996). "The Cyclical Behavior of Job Creation and Job Destruction: A Sectoral Model," *Economic Theory*, 7:95–112.

8. Griliches, Zvi (1957). "Hybrid Corn: An Exploration of the Economics of Technological Change," *Econometrica*, 25(4): 501–522.

9. Groshen, Erica L. and Simon Potter (2003). "Has Structural Change Contributed to the Jobless Recovery?" Federal Reserve Bank of New York, *Current Issues in Economics and Finance*, 9(8): 1–7.

10. Jovanovic, Boyan and Glenn MacDonald (1994). "Competitive Diffusion," *Journal of Political Economy,* 102: 24-52.

11. Jovanovic, Boyan and Peter L. Rousseau (2003). "General Purpose Technologies," Manuscript: New York University.

12. Lilien, David (1982). "Sectoral Shifts and Cyclical Unemployment." *Journal of Political Economy,* 90: 777–794.

13. Lippi, Marco and L. Reichlin (1994). "Diffusion of Technical Change and the Decomposition of Output into Trend and Cycle," *Review of Economic Studies*, 61(2): 19–30.

14. Lucas Jr., Robert E., (1982). "Understanding Business Cycles," in *Studies in Business Cycle Theory*, London, England, MIT Press.

15. Weller, Christian (2004). "America's Jobless Recovery," progressive-trail.org/ articles/ 040130 Weller.shtml