Jobless Recoveries

David Andolfatto
Simon Fraser University

Glenn MacDonald
Washington University in St. Louis

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Abstract

Historically, when an economy emerges from recession, employment tends to grow with or soon after the recovery in GDP. 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 commentators have termed the 'jobless recovery.'

To many observers, a jobless recovery defies explanation since it violates both historical patterns and the predictions of conventional theory. However, we show that a recession followed by a jobless recovery is exactly what neoclassical theory predicts when new technology impacts different sectors of the economy unevenly and is slow to diffuse, and sectoral adjustments in the labor market take time to unfold.

1 Introduction

One of the familiar business cycle facts is that when an economy emerges from recession, employment tends to grow either contemporaneously with, or soon after, the recovery in GDP; indeed, this is some of the motivation for Lucas' (1982) famous declaration that "business cycles are all alike." But this key fact appears to be changing. Figure 1 plots the time path for real GDP (per adult) and employment (per adult) for the United States over the last thirty years (1972.4 – 2003.2). The sample period covers five periods of declining GDP and employment.[1] While employment invariably begins to fall along with GDP, in the first three recoveries employment growth resumes almost immediately, i.e., within one or two quarters, after GDP growth turns positive. However, during the two most recent recessions,

[1] The dating of recessions here differs slightly from the episodes identified by the NBER since ththe NBER uses total rather than per capita GDP in its dating methodology.

employment growth has lagged the economic recovery by several quarters, leaving observers to puzzle over a phenomenon that has been labeled the "jobless recovery."

The phenomenon of an extended jobless recovery seems, to some, to defy explanation since it violates both historical patterns and the predictions of much conventional macroeconomic wisdom. In particular, the conventional view asserts that "aggregate demand" drives growth during a recovery. Since a major component of demand stems from the consumer and since a major component of household income comprises labor earnings, it is presumably the prospect of employment growth that fuels the economic recovery. Lack of employment growth during a recovery is, therefore, quite puzzling and problematic from this perspective. Some are even led to question whether a recovery in GDP is sustainable in the absence of employment growth. For example, according to Weller (2004): "Economic growth is more broad based than just a few quarters ago, with all economic industries contributing, which helps to stabilize and solidify the recovery. To maintain this momentum, though, the labor market has to improve. Otherwise, consumption, which comprises the vast majority of the economy, will not be able to grow at a strong pace, possibly putting a damper on growth in the medium-term." Naturally, this way of looking at the jobless recovery influences discussions of economic policy. For example, Bernstein (2003) writes "The jobs picture is so serious that steps to stimulate the economy and generate job growth are urgently needed. Any stimulus proposal should be evaluated primarily on its impact on job creation and its ability to reverse the current trend of weakening wage growth."

A jobless recovery, as a matter of arithmetic, obviously implies growth in labor productivity. Rising labor productivity is generally viewed as a positive development. But some take the view that increases in labor productivity may have undesirable consequences in the short-run. For example, according to Governor Ben Bernanke (2003): "Strong productivity growth provides major benefits to the economy in the longer term, including higher real incomes and more efficient and competitive industries. But in the past couple of years, given erratic growth in final demand, it has also enabled firms to meet the demand for their output without hiring new workers. Thus, in the short run, productivity gains, coupled with growth in aggregate demand that has been insufficient to match the expansion in aggregate supply, have contributed to the slowness of the recovery of the labor market."

We see several problems with explanations like those offered by Bernanke. First, the explanation takes as given an 'insufficient and erratic growth in final demand.' Assuming that 'final demand' is a well-defined concept, why should it's growth be insufficient and erratic? One possible explanation for an 'insufficiency' of aggregate demand is based on the notion of 'sticky' product prices. If prices are sticky, then a period of rapid productivity growth increases profit margins and allows firms to meet available demand with fewer workers. But this explanation is implausible since it requires a degree of price stickiness (i.e., several quarters) that is inconsistent with the data; e.g., see Bils and Klenow (2002).

In this paper, we offer an alternative explanation for the jobless recovery. Our explanation is related to Lilien's (1982) 'sectoral shifts' hypothesis, which argues that periods of high unemployment are largely the result of shocks that rearrange the relative demands for labor across different sectors of an economy. We argue that a likely candidate for these 'structural' disturbances are positive technological developments that favor some sectors over others.

However, costs to adjusting the economy's labor input is not in itself sufficient factor to explain a jobless recovery. Consider, for example, a standard mulitisector RBC model with labor market adjustment costs; e.g. Greenwood, MacDonald and Zhang (1996). A positive sectoral technology shock causes output and employment to move in the opposite direction only in the impact period of the shock. The subsequent transition dynamics for GDP are governed largely by the transition dynamics in the labor input. In other words, output and employment tend to move in the same direction in the periods following the shock.

One criticism of the RBC model is that, to the extent that movements in TFP are generated by the random arrivals of new technology, it seems implausible to suppose that any given technology shock diffuses instantaneously as is conventionally modeled. Instead, it seems more plausible to suppose that new ideas spread more like a contagion. Certainly, there is ample micro-level evidence that documents the well-known S-shaped diffusion pattern of new technologies; e.g., Griliches (1957). As well, 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. Motivated by arguments such as these, Andolfatto and MacDonald (1998) use a neoclassical growth model to demonstrate how the arrival and slow diffusion of new technology can generate booms and slowdowns in output that are roughly consistent with the data. However, since intertemporal substitution is the only source of employment dynamics in that work, the model has more limited success in accounting for employment dynamics, and shows little promise of explaining a jobless recovery.

Thus, adjustment costs in labor and technology adoption taken in isolation are not able to explain a jobless recovery. But there is reason to believe that neoclassical theory may be able to deliver the goods when both adjustment costs are present, as is plausibly the case in reality. In fact, we find that not only is neoclassical theory consistent with the phenomenon of a jobless recovery, but that it also offers an explanation as to how technological advances may lead to the recession that precedes the jobless recovery. The basic idea is as follows.

Consider the arrival of a new technology whose application has more impact in some industries than others (e.g., synthetic nitrogen fertilizers, robotics, the transistor, or IT, etc.). The new technology is initially applied by very few firms, but there are many other firms (in the more-impacted industries) that are eager to learn and implement it. To the extent that implementation is endogenous (which we assume), resources are diverted away from production toward general "learning activities." This diversion itself, along the lines of our earlier work, may lead to some contraction of output in the impacted industries. But since the new technology is slow to diffuse, the technology shock initially has a modest impact on aggregates. As the new technology becomes more widely used, productivity in the favored industries begins to rise, increasing those industries' demand for labor. The alteration in the structure of labor demand creates inter-industry wage differences, which provides the incentive for labor market adjustments. Since it takes time for labor to be reallocated from declining to expanding industries, however, unemployment (employment) must initially rise (fall), contributing further to the decline in aggregate output. At this stage, the economy enters into recession since the moderate increase in productivity is not enough to compensate for the decline in employment. The next phase of the cycle begins as the rate of technology diffusion peaks. At this stage, productivity is rising very rapidly while employment continues to contract as the economy continues to "restructure." Productivity growth, however, more than compensates for the weakness in the labor market, so that aggregate output begins to grow. The economy experiences a "jobless recovery." Eventually, the pace of labor reallocation begins to decline, so that employment begins to recover. Productivity growth remains positives, but begins to slow down as the new technology approaches full absorption. At this phase of the cycle, both output and employment are growing; i.e., the economy enters into a full expansion phase (with declining industries continuing to suffer). The cycle completes its course as the new technology is fully implemented. At this stage, both output and employment growth approach their normal levels.

The balance of the paper is organized as follows. Section 2 sets out the basics of the economic environment, and Section 3 details the assumptions we make concerning the economy's adjustment technologies. Section 4 characterizes the optimizing behavior of workers and firms, and characterizes the economy's general equilibrium. Section 5 discusses the model's parameterization. Section 6 reports the economy's response to a technology shock under the benchmark parameterization and shows that the model easily delivers quantitatively important jobless recoveries in response to technology change that impacts productive capabilities unevenly. Sensitivity analysis reveals that the extent and duration of a jobless recovery depends primarily on the scope of the technology shock. Section 7 concludes.

2 Basics

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 to either 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 production locations or industries; for brevity we will refer to these as locations. Each location is permanently endowed with $k > 0$ units of a location-specific factor of production, e.g., immobile land or capital. Since k is distributed uniformly over the unit interval, k represents both the aggregate and location-specific quantity of the fixed factor. For simplicity, we assume that each individual owns an equal share of the economy-wide stock k.[2]

Production at every location is described by the neoclassical production technology $y = F(k, n)$, where y denotes (homogeneous and nonstorable) output, k denotes the location-specific factor, n denotes the level of employment, and F is linear homogeneous, and so has diminishing marginal product in each factor.

There is a perfectly competitive labor market at each location. Assuming labor is freely mobile across locations, the equilibrium wage at each date and location is $w^0 = F_n(k, 1)$, with the population distributed uniformly across locations. Consumption and output for each individual is $c = y = F(k, 1)$.

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 major new technology is discovered that improves production possibilities at some fraction μ ($0 < \mu \leq 1$) of locations. The parameter μ indexes the *scope* of the new technology. If implemented at some location within the scope, new technology augments the productivity of k by the factor γ ($\gamma > 1$); production possibilities at these locations 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 locations 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 $j = 1, 2$. If the economy could adjust instantly to the new technology, then the new equilibrium would be immediately characterized by the following

[2] The only substantive role k plays in the analysis is to distribute profits. The reader can assume $k \equiv 1$ if desired.

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 final two describe market clearing in the labor and goods markets respectively. Clearly, $n^*(1) > 1 > n^*(2)$, 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 the capital-labor ratio increases.

3 Adjustment Technologies

Realistically, it takes time for firms to adopt major new ideas, and it takes time for workers to find more attractive jobs. To describe this process, we introduce two "adjustment" technologies.

3.1 Job search

We assume labor is perfectly mobile within a sector, but not across sectors. In order to move to another sector, an individual must spend at least one period searching (and not working) for a job in the other sector; note that a searcher would fit the CPS definition of unemployment. After a period of search, the individual has either been successful in finding employment, which we assume occurs with exogenous probability $1-\phi$, or not. Those whose search has failed can either return to their old job at the prevailing wage rate, or continue to look for work in the other sector.

To describe how the size of the workforce evolves in each sector, we anticipate some equilibrium behavior. First, no individual would choose to leave a location in the scope of the technology shock, i.e., in sector 1; any such location will generally attract workers from outside the scope. Consequently, the workforce will generally be expanding in sector 1 and contracting in sector 2. Second, the equilibrium will feature the same levels of employment and unemployment at each location within a sector.

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

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

3.2 Technology diffusion

Following Andolfatto and MacDonald (1998), when news of the 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 actually 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". For simplicity, suppose that when the new technology arrives, some (small) fraction $\lambda_0 > 0$ of firms in industry 1 are learn the new technology immediately and costlessly; we will treat λ_0 as a parameter.[3]

Assume that learning to implement the new technology takes time and resources, and is not fully predictable (at the firm level). Let e_t denote 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

[3]The assumption that an exogenous $\lambda_0 > 0$ firms learn is merely a convenience that allows us to model the diffusion of new technology as exclusively "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; Jovanovic and MacDonald (1994) explore innovation and imitation in detail.

workers must be paid a competitive wage. Given e_t, a low-tech firm successfully learns the technology, and so can use it in subsequent periods, with probability $\xi(e_t)\lambda_t$, where $0 \leq \xi < 1$ and $\xi' > 0 > \xi''$. The law of motion that describes the pattern of diffusion is then:

$$\lambda_{t+1} = \lambda_t + (1 - \lambda_t)\xi(e_t)\lambda_t. \tag{2}$$

Notice that the technology of learning is specified such 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 experience with learning how to implement the new technology. Accordingly, the diffusion of technology will follow an S-shaped pattern.

4 Individual Optimization and Equilibrium

In this section we characterize optimal behavior for individuals and firms. Since we are modelling behavior subsequent to 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.

4.1 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 $j = H$ 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 decide on the extent of effort to learn the new technology, e_t.

Let $V_t^j(1)$ denote the capital value of an optimizing firm in sector j at date t. The sequence $\{V_t^H(1)\}_{t=0}^{\infty}$ satisfies, for all t:

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

Likewise, for low-tech firms, the sequence $\{V_t^L(1)\}_{t=0}^{\infty}$ satisfies, for all t:

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

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

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

Clearly, 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 with the current state of technology absorption λ_t. Likewise, the demand for learning effort decreases with the cost $w_t(1)$ of employing workers in such an activity.

4.2 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 on the production line are paid the same as individuals employed in learning, 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:

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

The last two equations can be combined to determine whether any individuals search, and the level of unemployment. Define $W_t(2) \equiv \max\{J_t(2), Q_t\}$. Then $W_t(2)$ must satisfy:

$$W_t(2) = \max\{w_t(2) + \beta W_{t+1}(2), \beta\left[(1-\phi)J_{t+1}(1) + \phi W_{t+1}(2)\right]\}.$$

Since $w_t(2) = F_n(k, x_t(2) - u_t)$, we can write:

$$W_t(2) = \max\left\{F_n(k, x_t(2) - u_t) + \beta W_{t+1}(2), \beta\left[(1-\phi)J_{t+1}(1) + \phi W_{t+1}(2)\right]\right\}.$$

Thus, along the equilibrium path, u_t is determined by:

$$\begin{aligned} F_n(k, x_t(2) - u_t) + \beta W_{t+1}(2) &= \beta\left[(1-\phi)J_{t+1}(1) + \phi W_{t+1}(2)\right], \quad (8) \\ \text{if } J_t(2) &= Q_t; \\ \text{and } u_t &= 0, \ \text{if } J_t(2) > Q_t. \end{aligned}$$

In other words, for positive unemployment rates, the level of unemployment must adjust to a point so that a sector 2 individual is indifferent between working in sector 2 or searching.

4.3 Equilibrium

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

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

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

1. Given$\{w_t(1), w_t(2)\}_{t=0}^{\infty}$, the sequences $\{u_t, J_t(1), J_t(2), Q_t\}_{t=0}^{\infty}$ satisfy equations (7) and (8); i.e., households are optimizing;
2. Given $\{w_t(1), w_t(2), \lambda_t\}_{t=0}^{\infty}$, the sequences $\left\{n_t^H(1), n_t^L(1), e_t, V_t^H(1), V_t^L(1)\right\}_{t=0}^{\infty}$ satisfy equations (3), (4), (5) and (6); (firms are optimizing); and
3. The labor market in each sector clears at each date; i.e.,

$$\begin{aligned} &\lambda_t n_t^H(1) + (1-\lambda_t)(n_t^L(1) + e_t) = x_t(1) \quad (9) \\ &n_t(2) + u_t = x_t(2) \end{aligned}$$

5 Parameterization

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

$$\begin{aligned} F(\gamma^{\chi}k, n) &= (\gamma^{\chi}k)^{\alpha} n^{1-\alpha}; \\ \xi(e) &= 1 - \exp(-\eta e), \end{aligned}$$

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

Taking a time interval to be one year, we assume a standard value for the discount factor; i.e., $\beta = 0.96$. The parameter $\alpha = 0.36$, implying a long run labor share of income equal to 64%. The search failure probability is $\phi = 0.15$, yielding an expected unemployment duration of just over one year. The parameter η governs the speed at which the new technology diffuses; setting $\eta = 10$ implies that it takes several years for a new technology to diffuse fully. Results will also be reported for different diffusion rates. Finally, let $k = 1$.

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

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 25%. In our benchmark parameterization, we set $\mu = 0.25$ and $\gamma = 4.5$.

6 Results

6.1 Benchmark Parameterization

Recall that the initial condition features full employment, with sector 1 and 2 employment shares equal to 25% and 75%, respectively. The initial wage rate is equal across sectors and is equal to 0.64 (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 labor productivity by just over 70% (i.e., by a factor of $4.5^{0.36}$). 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 TFP is miniscule.

The top panel of Figure 2 displays the impulse-response functions for employment (in each sector) and unemployment, while the bottom panel displays the impulse-response functions for sectoral wage rates and economy-wide unit cost. Initially, the technology shock has no effect on intersectoral flows, even though the real wage in industry 1 begins to rise immediately (albeit, modestly at first). Unemployment begins to rise modestly three years (in period 4) following the arrival of the technology shock. At this stage, the real wage in industry 1 has risen enough to attract searchers. As the real wage continues to rise rapidly in industry 1, so does unemployment (sector 2 workers choosing to search for work in sector 1). The real wage in industry 2 rises as well, as the drain of workers from industry 2 increases the marginal product of labor. Unemployment peaks a full eight or nine periods following the shock and then begins to decline, eventually reaching its normal level (zero, in this model) a full thirteen periods following the shock. In the long-run, industry 1 (which comprises only 25% of the firms in the economy) is employing over half of the workforce. The model also predicts some interesting dynamics in sectoral wage differences, with wage dispersion displaying a U-shaped pattern over the transition period.

Figure 3 displays the impulse-response functions for GDP growth and employment growth. Since the new technology is initially implemented by a small number of firms, output and employment decline modestly on impact. But soon after the shock, significant resources are diverted away from production. In sector 1, workers are removed from the production line and devoted to activities that are designed to implement the new technology. In sector 2, some workers are compelled to leave their current jobs for the prospect of better opportunities elsewhere. Since the diffusion of new technology proceeds slowly, so does productivity. Together, these facts imply an initial period of contracting GDP and employment; i.e., the economy enters into a recession (or at least, a period of below normal growth).

GDP growth turns positive five periods following 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 very rapidly. The rapid adoption of technology leads to a surge in productivity growth. Evidently, this rapid spread of new technology serves to stimulate the pace of sectoral readjustments in the labor stock 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.

6.2 Sensitivity Analysis

In this section, we examine the sensitivity of the model's impulse response functions to various parameter purtubations. In the first experiment, we increase the ease with which firms may acquire the newly available technology by increasing η by a factor of 100. The result is depicted in the top-left diagram of Figure 4. Predictably, the new technology diffuses much more quickly. However, the general pattern of recession followed by a jobless recovery remains intact.

The top-right diagram of Figure 4 records the transition dynamics for GDP and employment growth rates when the new technology has wide scope. In this experiment, we set $\mu = 0.99$ (and reduce γ such that long-run GDP increases by 25%). This type of technology shock benefits almost every sector in the economy, so that virtually no sectoral labor market flows are required as the economy absorbs the new technology. 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, a broad scope technology shock is unlikely to induce a jobless recovery.

Finally, the bottom two panels report how the predictions of the model vary with the exogenous job-finding probability $1 - \phi$. We used $\phi = 0.15$ in the benchmark parameterization. The bottom-left panel of Figure 4 uses $\phi = 0.25$ and the bottom-right panel uses $\phi = 0.05$. These different parameter values have some quantitative impact on the nature of the cycle, but the general pattern of recession followed by jobless recovery remains intact.

6.3 An Oil Price Shock

Based on the results reported above, one may be led to believe (as suggested by Groshen and Potter, 2003) that jobless recoveries should follow anytime an economy experiences an unusually high degree of intersectoral reallocation of labor. But this need not be the case. We know, for example, that U.S. economy was afflicted by a number of sectoral disturbances in the 1970s (primarily, oil price shocks) that contributed to episodes of recession and unemployment, but which were not characterized by jobless recoveries.

In the context of our model, we can think of an oil price shock as a negative TFP shock concentrated in a subsector of the economy. Because energy intensive sectors must react virtually instantaneously to higher energy prices, it is appropriate to think of this TFP shock as diffusing instantaneously throughout the affected sectors. To see how such a shock affects behavior in our economy, assume that 75% of firms subject to a 25% decline in TFP (with all other parameters corresponding to our benchmark parameterization). As Figure 5 demonstrates, this type of shock sends the economy into recession, with both GDP and employment declining together. The transition dynamics are characterized by a relatively short restructuring period, but both GDP and employment move together over the transition period; i.e., there is no jobless recovery.

The point of this exercise is to show that there may be other factors in the world that lead to recessions and intersectoral readjustments, so that 'sectoral shifts' in themselves need not be associated with a jobless recovery.

7 Conclusions

It is an empirical fact that the pattern of economic development in advanced economies is characterized by growth and fluctuations in GDP. Virtually no one disputes the role of technological advancement in generating growth. 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.

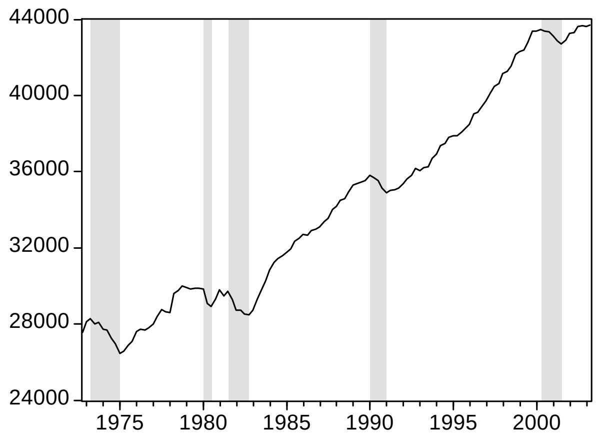
In this paper we explored the properties of an RBC model in which growth is driven by technological advances that improve factor productivity, that vary in the degree to which they affect the structure of the economy, that do not diffuse instantaneously, and that generate lasting intersectoral labor market flows. 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.

While advances in the technological frontier are initially characterized by recessions (or growth slowdowns) in our model, we of course are not willing to argue that all recessions are generated by technology shocks. We are merely suggesting that technology shocks that diffuse slowly and require sectoral readjustment may be a contributing (and possibly primary) factor in some past recessionary episodes. Nor are we claiming that all forms of discovery necessarily lead to recessions and jobless recoveries. Whether or not this happens appears to depend primarily on the scope of technological advance.

Of course, this leaves open the intriguing question of what factors determine the attributes of technological developments in terms of their size, scope, and ease of implementation. The fact that, according to our scope-based explanation of recently observed dynamics, new technology is systematically narrower in scope but greater in magnitude suggests the recent trend may not be serendipitous.

FIGURE 1

Real GDP per Adult (1996 US$)
United States 1972.4 - 2003.2



Employment per Adult (%)
(Household Survey)
United States
1972.4 - 2003.2

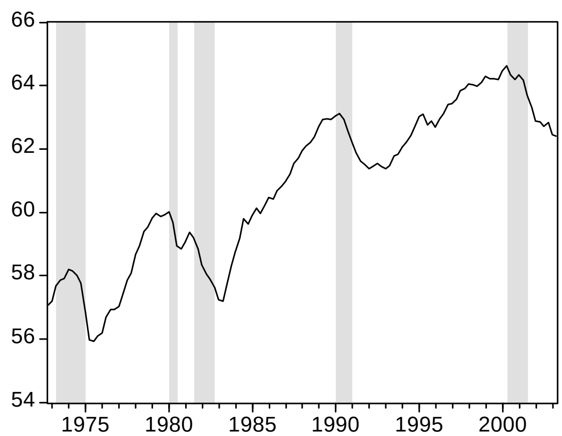


FIGURE 2

Sectoral Labor Flows and Wages
Benchmark Parameterization

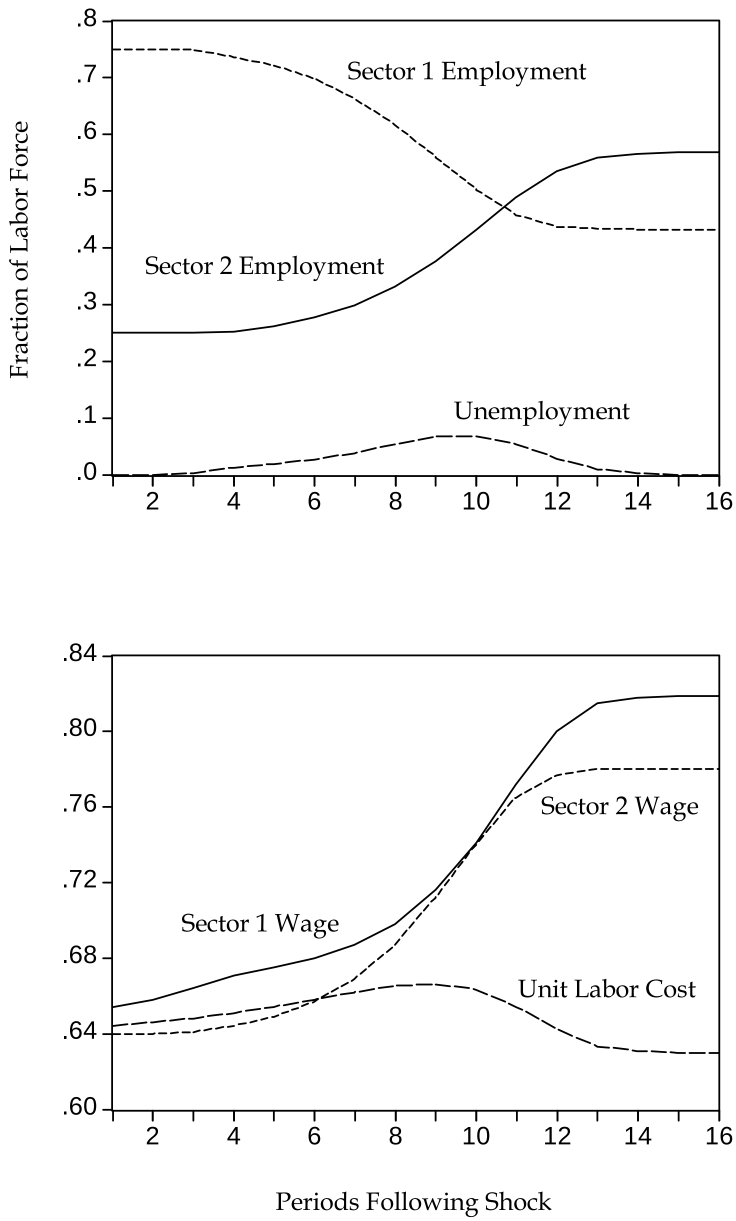


FIGURE 3
GDP and Employment Growth
Following a Technology Shock
Benchmark Parameterization

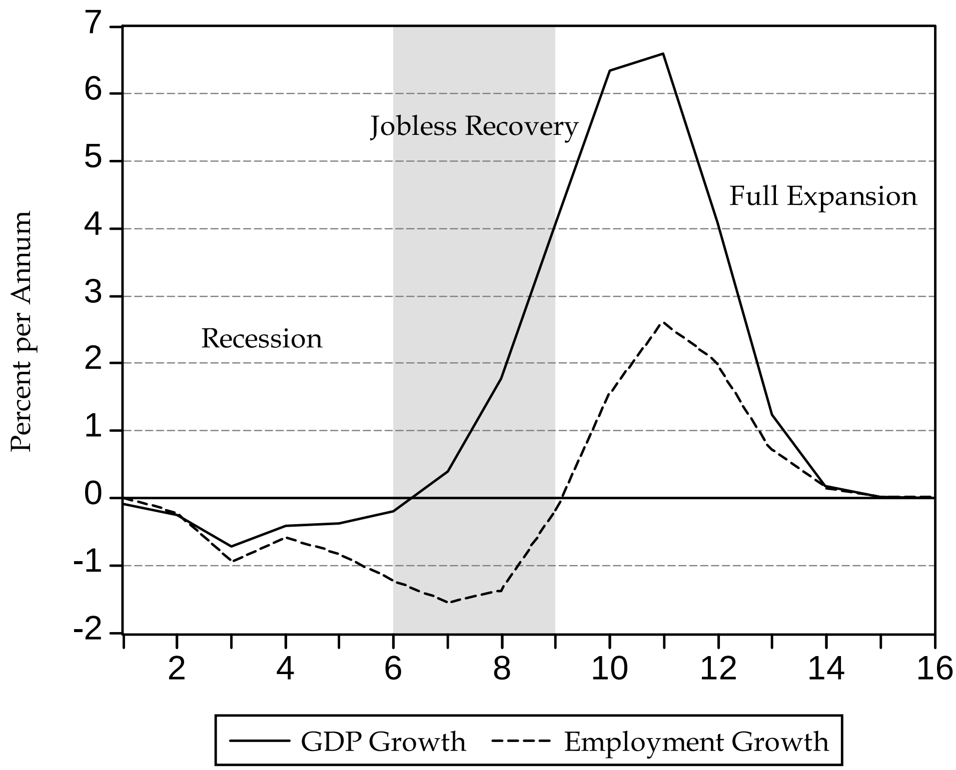


FIGURE 4

GDP and Employment Growth
Following a Technology Shock
Sensitivity Analysis

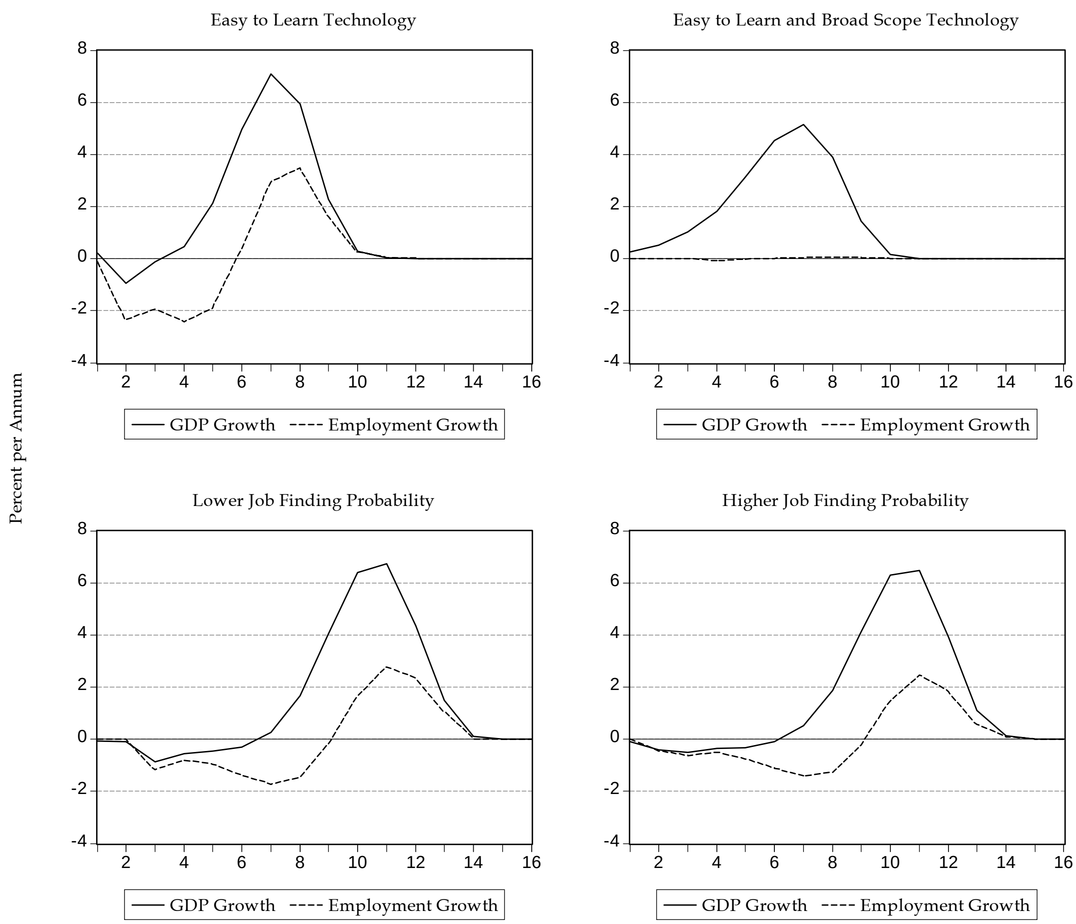
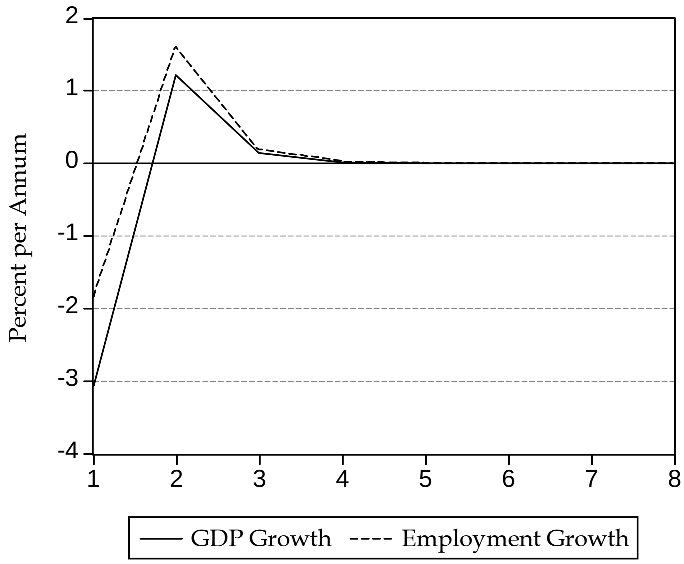


FIGURE 5

GDP and Employment Growth
Following an Oil Price Shock



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