MARCH/APRIL 1991

ECONOMIC PERSPECTIVES

A review from the
Federal Reserve Bank
of Chicago

**Hog butchers no longer:
20 years of employment change
in metropolitan Chicago**

**Technology shocks and
the business cycle**

**1991 Bank Structure
Conference program
highlights**

FEDERAL RESERVE BANK
OF CHICAGO

Contents

ECONOMIC PERSPECTIVES

MARCH/APRIL 1991 Volume XV, Issue 2

ECONOMIC PERSPECTIVES is published by the Research Department of the Federal Reserve Bank of Chicago. The views expressed are the authors' and do not necessarily reflect the views of the management of the Federal Reserve Bank.

Single-copy subscriptions are available free of charge. Please send requests for single- and multiple-copy subscriptions, back issues, and address changes to Public Information Center, Federal Reserve Bank of Chicago, P.O. Box 834, Chicago, Illinois 60690-0834, or telephone (312) 322-5111.

ISSN 0164-0682

Hog butchers no longer: 20 years of employment change in metropolitan Chicago

Philip Israilevich and
Ramamohan Mahidhara

Over the last two decades, the Chicago metropolitan area has seen substantial changes in its manufacturing and service sector employment. Manufacturing employment declined by almost 300,000, while service employment rose by about 500,000 between 1970 and 1987.

Why did this happen? One possibility is that the productivity of workers in manufacturing firms increased and that of workers in service firms did not. Another possible explanation for the change in Chicago's employment patterns is that manufacturing firms may have contracted out many jobs that used to be done in-house, hence jobs which used to be classified as manufacturing are now classified as service. Finally, the decrease in manufacturing jobs and the increase in service jobs could have been caused by a change in consumer preferences. For example, an aging population may demand more health care and fewer skateboards, causing increased employment in the health care industry and decreased employment in the skateboard industry.

Effective policy decisions depend upon an accurate prediction of future employment trends. It makes sense to think that future employment trends could be predicted more accurately if the causes of employment change are understood. Hence, it is important for policy makers to understand the reasons for changes in employment.

In this article, we present the results of research into the causes of employment change in metropolitan Chicago over the last 20 years. Our results are obtained from a detailed economic model developed at the Regional Economics Applications Laboratory (REAL).[1] Using the model to identify the forces underlying employment changes in metropolitan Chicago over the last two decades, we found that changes in consumer preferences were the major cause of employment increases in the services industry.

We begin the second section of this article by discussing the importance of the service sector. We review the debate concerning the decline of manufacturing employment and the growth of service employment. In the third section, we present our methodology and the model itself. In the fourth section, we analyze the results obtained from our simulations. Conclusions are presented in the final section of the article.

Philip Israilevich is an economist at the Federal Reserve Bank of Chicago and Associate Director of the Regional Economics Applications Laboratory. Ramamohan Mahidhara is a Senior Research Associate at the Regional Economics Applications Laboratory and an Adjunct Assistant Professor at the Institute of Government and Public Affairs, University of Illinois
The authors thank David Allardice, Bill Byers, Geoff Hewings and participants at the November 1990 Regional Science Association Meetings (Boston) for comments and suggestions. Thanks are also due to the Economic Development Commission of the City of Chicago for supporting the Chicago Region Econometric Input-output Model, as well to Dr. Robert McGuckin of the Center for Economic Research at the U.S. Bureau of Census for allowing access to the Longitudinal Research Data (LRD).

The importance of the service sector in analyzing changes in employment

Traditionally, economists viewed manufacturing firms as *basic* industries, which form the nucleus of the economy around which peripheral sectors revolve. According to the traditional view, peripheral sectors are inextricably linked to the manufacturing sector, growing when manufacturing grows and declining when manufacturing declines. However, the traditional view has been undermined by evidence that the service sector can grow when manufacturing either stagnates or declines.

The idea that manufacturing is the primary force in any economy is slowly changing in the public's perception, possibly due to the unprecedented growth in service employment. But the causes underlying rapid growth in services are not well established. Because the number of jobs in the service sector exceeded those in the manufacturing sector on the national level less than a decade ago, there has been relatively little research into the causes and implications of such growth.[2] Analysis of the cause of growth in the service sector at the regional level is hampered further by the lack of data.

It is often suggested that the employment growth in services and the employment decline in manufacturing is primarily a statistical illusion attributable to manufacturing firms closing down their auxiliary divisions and shifting the work to outside firms in the service industry. This shift in employment is called *unbundling* (Kutscher 1988). For example, a manufacturing firm could reduce the size of its accounting department and hire an accounting firm to do the same job. Consequently, the manufacturing sector loses some employees and the service sector gains some employees. However, according to the unbundling hypothesis, this reshuffling does not reflect either a real growth in services or a real decline in manufacturing. The unbundling hypothesis is important because it raises questions about the type of growth in the service sector, and more importantly, whether the service sector is growing at all.

In the last few years, researchers have looked more closely at the service sector through the analysis of occupational shifts.[3] The results indicate that unbundling plays a very small role in the expansion of the service sector. Researchers have shown that unbundling accounted for only about two percent of total employment growth in services. However, the unbundling argument is still popular in the media.

In an earlier study (Israilevich and Mahidhara 1990), we discussed the growth of the manufacturing and service sectors in the Chicago metropolitan area. According to our study, manufacturing and services appear to have followed two largely independent growth paths in Chicago between 1972 and 1987. While manufacturing output fluctuated substantially over the period of our study, manufacturing output in 1987 was about the same as in 1972, in real terms. Manufacturing employment and income, however, declined noticeably. Employment in 1987 was about two-thirds of its 1972 level, while income was about three-fourths of its 1972 value. For the service sector, however, output, employment and income grew steadily between 1972 and 1987. Service output, employment, and income all approximately doubled between 1972 and 1987. Thus, growth in Chicago's service industry was mostly independent of the manufacturing sector. In this article, we continue our investigation of employment in Chicago. We present results of recent research concerning employment changes and their causes in manufacturing and services.

Economic sectors and the causes of employment growth

We divide the economy into three sectors: resources and construction, manufacturing, and services. Resources include agricultural services, forestry, fisheries, and mining. Services consist of TCU (transportation, communications, and utilities), trade, FIRE (finance, insurance, and real estate), and personal and business services. We also single out the personal and business service sector in order to compare its progress with the other three broader categories.[4]

We investigated three important causes of changes in employment:

1) labor productivity,
2) business practices, and
3) final demand.

An increase in labor productivity causes a decrease in employment per unit of output. As workers' skills and training are enhanced and the equipment they work with becomes more productive, output per worker rises. Constant and noticeable improvements in labor productivity are fairly common in many manufacturing industries; they are somewhat less common in personal and business services. One reason for this difference is that measurement of productivity in the service sector is difficult and controversial.

Changes in business practices can cause changes in employment. Business practices are the ways in which firms produce their goods and services. They reflect the pattern of inputs, such as labor, that firms use in order to produce their output(s). Over time, with changes in technology, changes in relative prices of inputs and regulations and industry structure, firms change their business practices and hence their demand for labor, among other things (Kutscher 1988). For example, as an economy passes from an industrial to a post-industrial stage, the demand for manufactured goods is likely to fall and the demand for services likely to rise. Unbundling is one example of a change in business practice. Unbundling occurs when firms contract out work that was hitherto done within the firm. There are also business practice changes which do not constitute unbundling. For example, a new environmental regulation might cause a firm to switch to an alternative, less polluting technology, which may employ fewer people than before. In this article, we assume that *all* declines in manufacturing employment due to changing business practices constitute unbundling. We make this assumption in order to get an upper bound for unbundling.

Changes in final demand can cause changes in employment. Final demand consists of expenditures on consumption, investment, government and net exports (imports minus exports). Final demand affects employment growth by raising the demand for one sector's output and reducing the demand for a different sector's output (Kutscher 1988). There are two basic types of final demand changes: 1) a change in the size of final demand, and 2) a change in the composition of final demand. A change in the size of final demand results from a change in the size of the economy. For example, when an economy grows, its population may grow, thereby raising the demand for consumer goods, resources for investment, government services and net exports. A change in the composition of final demand results from a change in consumer preferences or firm capital formation requirements. For example, an aging population is likely to demand more personal and business services, such as health care and retirement housing. Or, the increasing participation of women in the labor force may raise the demand for personal and business services such as day care and, perhaps, fast food restaurants (Duchin 1988). This unbundling of household activities is similar to the unbundling of personal and business services in manufacturing. Furthermore, as the output of portable and durable services rises, the likelihood of exporting these services rises too. A portable service is one that can be transported across distances. For example, a business consulting firm based in Chicago may provide strategic planning services for a pension plan of a Connecticut-based firm. A durable service is one that retains its value and usability over time. For example, a computer-based inventory control software package retains its value over time.[5]

Often, an event affects both business practices and final demand. Consider a firm that purchases energy efficient motors. This purchase should lead to lower energy costs for the firm (a change in business practices) but also higher capital expenditures (a change in final demand). In addition, the new motors may raise labor productivity, which could also affect employment. These simple examples show that the economy has a complicated structure, and that a change in employment often has a cause which is more complicated than a mere expansion or contraction of the economy.

Econometric and input-output models

Employment changes occur when firms are created or dissolved, and when firms expand or contract. In order to analyze these changes, we need to distinguish between the direct and indirect effects that firms can have on employment. Suppose that a firm expands and hires 10 new workers. This is an example of a direct effect. To give a very simple example of an indirect effect, suppose further that as a consequence of expansion, the firm demands more supplies. As a result, the supplier expands its operations and hires 5 new workers. It is easy to see that estimating the indirect effects in a realistic case would be very complicated. In order to estimate both the direct and the indirect effects that a firm typically has on Chicago metropolitan employment, we use input-output analysis and econometric modeling. Our method is valid for analyzing changes in economy-wide employment, because total economy-wide employment is the sum of individual firms' employment.

Companies interact with each other and final consumers (consumers within and outside of the region, governments, and investment agents) via purchases and sales. Because the transactions of a buyer (purchases) and a seller (sales) represent two sides of the same transaction, it is not necessary to record both. We choose to record only purchases. For our study, we tabulate the purchases made by industries from other industries and from individuals. We record these purchases as shares of total expenditures, rather than as dollar values.[6] The input-output table is in matrix form, with rows depicting selling sectors and columns representing purchasing sectors. Thus, going down any column of an input-output table, one can see what proportion of a particular sector's output is accounted for by purchases from other sectors. These shares represent a purchasing pattern of inputs necessary to produce one dollar's worth of the sector's output. A given share multiplied by the total revenue represents the total dollar purchase of a given input by the sector (see Figure 1 for a simple illustration).

In this study, we compare input-output tables representing the Chicago economy during the two historical periods, 1972-79 and 1980-87. This is done in order to compare the Chicago economy before and after 1980—the year in which service employment exceeded manufacturing employment in Chicago.

Typically, consistently recorded input-output tables for different years are not available for regional economies.[7] We generated input-output tables using simulations from the Chicago Region Econometric Input-output

FIGURE 1

Input-output table

Sales/purchases	Resources & construction	Manufacturing	Services	Final demand	Total output (sales)
Resources & construction	10	15	15	60	100
Manufacturing	20				
Services	25				
Value added and other payments	45				
Total output (revenue)	100				

SIMPLE PICTURE OF INPUT-OUTPUT TABLE. We present a hypothetical transaction flows table from which the table of input-output coefficients can be derived. For simplicity, we present and interpret data for only one sector (resources and construction); a similar interpretation holds for all other sectors. The values in the second column of the table represent purchases by the resource and construction sector. Thus, in order to produce $100 worth of output (revenue), the resource and construction sector purchases $10 worth of goods from itself, $20 worth of goods from the manufacturing sector, and $25 worth of goods from services. The remaining $45 consists of value added to output via extraction or construction, wages paid, and other payments. The values in the second row of the table represent sales by the resource and construction sector to all other sectors in the economy. Thus, the resource and construction sector sells $10 of goods to itself, $15 to the manufacturing sector, $15 to the service sector, and $60 to the final demand sector. Adding up across the row, we get total output (sales) equal to $100.

Model (CREIM). These tables represent the average technology for Chicago over each period. See Box 1 for details of CREIM.

Analysis

In order to determine the changes in employment over time in different sectors, we need to compare input-output tables at different points in time. The data for Figure 2 were obtained by subtracting the 1972-79 input-output table from the 1980-87 input-output table. Note that Figure 2 represents only the changes in direct expenditures, that is, the changes in business practices across the two periods.

Figure 2 illustrates the percentage changes in the consumption of personal and business services and manufacturing goods by all industries across the two periods. The figure shows that all sectors of the economy demanded more personal and business services per unit of output in the second period than in the first. The sharpest rise in demand for personal and business services per unit of output was in the services sector (TCU, TRD, FIRE, and personal and business services). At the same time, demand for manufacturing goods per unit of output declined among all sectors, no doubt resulting in the decline in manufacturing employment.

Box 1: The Chicago Region Econometric Input-output Model

The Chicago Region Econometric Input-output Model, or CREIM, combines detailed inter-industry information (obtained from the input-output table) with time series data (obtained from the econometric model). Input-output tables model purchases and sales in an economy. However, these models can not adequately describe changes over time. On the other hand, econometric models do not have enough data to describe detailed inter-industry relationships. Therefore, the combination of these two models results in a comprehensive model for the Chicago economy, capable of predicting changes in final demand and business practices, along with all other variables typical of regional econometric and input-output models. Key aspects of CREIM are presented below.[8]

The geographical coverage of our study is the six county Chicago metropolitan region consisting of Cook, DuPage, Kane, Lake, McHenry, and Will counties. Currently formulated on a one-digit Standard Industrial Classification (SIC) code basis, CREIM has eight private industrial sectors and three government sectors. The model has 50 behavioral equations, 9 identities, 59 endogenous variables, and 30 exogenous variables. It is set up for annual long term projections.

In CREIM, the Chicago economy faces two sets of demands: (1) exports going outside the region constituting *external* demands, and (2) demands from the various economic sectors within the Chicago economy constituting *internal* demands.

In the first stage, exports are estimated using national GNP figures. Exports for individual industries in Chicago are linked to the same industries at the national level. Projections for all exogenous variables (including GNP and U.S. industrial output) are obtained from Data Resources Incorporated (DRI). In the second stage, as firms respond to external demand, they give rise to a set of local inter-industry demands. The individual output equations capture these internal demands using input-output relationships. Unlike many other models which use national input-output coefficients, CREIM uses coefficients from a Chicago-specific input-output model (also constructed at REAL). Inter-industry coefficients are adjusted for time changes, allowing for new inter-industry relationships every year.

Forecasts of output (obtained using national data and exports) are combined with forecasts of labor productivity and wage rates to predict employment and earnings by industry. These projections are combined with projections of the labor force participation rate and the unemployment rate to obtain population forecasts. Total earnings are obtained by predictions of property income, transfer payments, residence adjustments, and personal contributions to social insurance. Total earnings are then combined with population forecasts to obtain estimates of personal income. This completes the first set of demands, that is, external demands.

The personal income and population figures obtained above are used to estimate the final demand sector, which consists of consumption, investment, and government purchases. In the analysis, four types of consumption expenditures and three types of investment expenditures are considered, along with one type of state and local government expenditure.

Initially, the entire stimulus to the Chicago economy comes from external demand, that is, exports. For example, an increase in the nation's

The evidence in Figure 2 explains why manufacturing employment in Chicago declined and employment in personal and business services increased from period 1 to period 2. However, we cannot tell from Figure 2 whether this is due to a real shift in employment or is just a statistical reshuffling as proponents of the unbundling hypothesis claim. The fact that the manufacturing sector itself reduced its consumption of manufactured goods and raised its consumption of personal and business services supports the view that changing business practices, i.e., unbundling, were responsible for at least some of the change in employment. However, Figure 2 does not show the relative effects of changes in labor productivity, final demand and business practices on employment. Also, Figure 2 only accounts for direct, first order impacts, and does not include the indirect effects of employment change in any given industry. These issues are addressed by the analysis in Tables 1 and 2.

Average total employment in Chicago rose from 3.048 million in the first period (1972-79) to 3.279 million in the second period (1980-87), an increase of about 7.6 percent. As shown in Table 1, this total growth of 7.6 percent can be broken up into growth from each of the three economic sectors—resources

GNP would lead to an increase in exports from the Chicago region. As explained in the preceding steps, this increase in exports would feed into the input-output model, which would then give rise to a set of inter-industry demands. The increase in output would give rise to an increase in employment, and thus earnings. Given labor force participation rates, the rise in employment would give rise to an increase in population. The rise in population and earnings leads to an increase in personal income, which is reflected in rising personal consumption, investment, and state and local government expenditures. This increase in personal income now gives rise to a second set of demands driving the model, that is, final demand from within the Chicago economy.

The modeling cycle is completed when the above described final demand feeds into the output sector. The increase in final demand further raises output. This time though, the output increase comes about in response to increased *internal* demand for goods and services, both private and public, and not in response to a demand for exports coming from outside the Chicago economy. This increased demand works its way through the input-output model in exactly the same way as exports did, resulting in another chain of increases in output, earnings, employment, population, income, and ultimately, final demand. What we see here is a multiplier effect at work. This process continues, and at each stage, the multiplier effect grows smaller and smaller. After several iterations, the model converges, and we obtain figures on the employment, output, and income impact of increased exports.

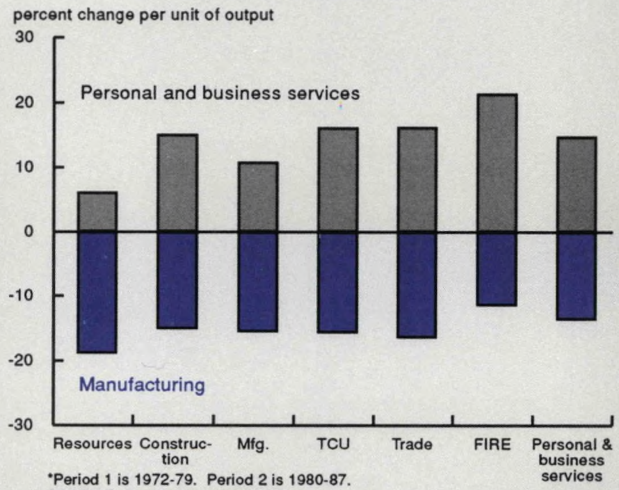
The input-output block of CREIM is a conventional, static input-output model. It differs from other conventional regional input-output models, which are typically constructed by regionalizing a national input-output model. In our input-output block, we use unpublished, establishment-based, Chicago-specific information for the manufacturing block. These data on industrial purchases and sales are obtained from the U.S. Bureau of Census.[9]

The two input-output tables generated for this article correspond to the periods 1972-79, and 1980-87, and should be viewed as representing the average technology across each of those periods. The tables are generated from CREIM in the following manner. An input-output table, say A, represents a matrix of expenditure shares for the various inputs. We then obtain the *Leontieff inverse B*, as $(I-A)^{-1}=B$, where I is the identity matrix. Elements of the Leontieff inverse represent the effect of a unit change in final demand on the output of each industry, that is each element, b_{ij}, of B is a partial derivative of the change in industry output to the change in final demand. Final demand is represented by the vector $Y = y_j$. Using these notations, $b_{ij} = \partial(x_i)/\partial(y_j)$, where the output vector $X = x_i$, and $i,j = 1,...,n$, denote the sectors in the economy.

Elements of the Leontieff inverse b_{ij} were generated by running a number of simulations using CREIM. We ran two sets of simulations, one for each period. Within each period, we investigated the impact of $1 billion annual increase in real output for each of the following eight sectors: resources, construction, durable manufacturing, nondurable manufacturing, TCU, trade (TRD), FIRE, and personal and business services. From these simulations, we obtained total and partial output multipliers, which were then used to construct our input-output tables as explained in Box 2.

FIGURE 2

Change in business practices from Period 1 to Period 2*



*Period 1 is 1972-79. Period 2 is 1980-87.
SOURCE: Simulation using CREIM.

and construction, manufacturing, and services (TCU, trade, FIRE, and personal and business services). Box 2 provides the derivations underlying Tables 1 and 2.

A small increase in resources and construction employment from the first period to the second caused total employment to rise by about 0.2 percent. Increases in services employment were significant, leading to a 12.9 percent rise in total employment. Thus, employment gains in the resources and construction and services sectors caused overall employment to rise by 13.1 percent from the first to the second period. These gains were diminished, however, by a sizeable drop in manufacturing employment from period 1 to period 2. This drop in manufacturing employment pulled total employment down by about 5.5 percent. The sum total of changes in these three sectors (+0.2 percent, +12.9 percent, -5.5 percent) resulted in total employment in the second period rising by about 7.6 percent relative to the first.

According to Table 1, changes in labor productivity resulted in a 3.8 percent decline in total employment. Of that 3.8 percent decline, improvements in manufacturing labor productivity accounted for 2.8 percent, while the remaining 1 percent was caused by improvements in service sector labor productiv-

TABLE 1

Decomposition of employment growth

	(1)	(2)	(3)	(4)	(5)	(6)
	Period 1* employment decomposition $\hat{\mu}_1 B_1 Y_1$	Labor productivity effects $\Delta\hat{\mu} B_1 Y_1$	Business practice effects $\hat{\mu}_2 \Delta B Y_2$	Final demand effects $\hat{\mu}_2 B_1 \Delta Y$	Period 2** employment decomposition (5)=(1)+(2)+(3)+(4)	Rate of growth (6)=(5)-(1)
	(fraction of total employment)	*(----change from period 1 to period 2----)*				
Sectors						
Resources & construction	0.055	0.000	-0.000	0.001	0.057	0.002
Manufacturing	0.290	-0.028	-0.033	0.006	0.234	-0.055
All services	0.654	-0.010	0.036	0.103	0.783	0.129
Total	**1.000**	**-0.038**	**0.002**	**0.111**	**1.075**	**0.076**
Personal & business services	0.240	0.003	0.017	0.064	0.325	0.085

SOURCE: Simulation using the Chicago Region Econometric Input-Output Model (CREIM).
NOTE: Totals may not equal sum of components due to rounding errors.
*Period 1 is 1972-79
**Period 2 is 1980-87

TABLE 2

Decomposition of final demand effect on employment
(Rate of change from Period 1 to Period 2))

	Effects of change in composition $\hat{\mu}_2 B_1 \Delta Y_c$	Effects of change in size $\hat{\mu}_2 B_1 \Delta Y_s$	Total final demand effect $\hat{\mu}_2 B_1 \Delta Y$
Industry			
Resources	0.001	0.001	0.002
Construction	-0.006	0.006	0.000
Total resources & construction	**-0.005**	**0.007**	**0.002**
Manufacturing durable	-0.026	0.021	-0.005
Manufacturing nondurables	-0.001	0.011	0.010
Total manufacturing	**-0.026**	**0.032**	**0.006**
Transportation, communication, utilities	-0.001	0.008	0.007
Trade	-0.016	0.031	0.015
Finance, insurance & real estate	0.006	0.011	0.017
Personal & business services	0.035	0.030	0.065
Total all services	**0.024**	**0.079**	**0.103**
Total economy	**-0.007**	**0.118**	**0.111**

SOURCE: Simulation using CREIM.
NOTE: Totals may not equal sum of components due to rounding errors.

ity. As firms in both manufacturing and services became more productive, they needed fewer workers to produce the same amount of output.

Total employment grew by 0.2 percent as a result of changes in business practices. Sectorially, changes in manufacturing business practices resulted in a 3.3 percent drop in total employment. This was in contrast to a change in business practices in the service sector, which resulted in a 3.6 percent increase in total employment. The combined effect of changes in business practices and labor productivity caused total employment to decline by about 3.6 percent.

Changes in final demand had a dramatic impact on total employment, raising total employment by 11.1 percent in period 2 relative to period 1. This 11.1 percent rise was coupled with the above discussed 3.6 percent drop (caused by changing labor productivity and business practices) resulting in an overall increase of 7.6 percent in employment. As shown in the final demand column in Table 1, 10.3 percent of the total impact of 11.1 percent came from the services sector. Thus, over 90 percent of the final demand impact was caused by a change in final demand in the services sector. Table 1 also shows that within the services sector, a large proportion (58 percent) of the impact was caused by personal and business services.

Earlier, we observed that changes in the size of the economy led to changes in the size of final demand. We also observed that changes in consumer preferences and firm input requirements led to changes in the composition of final demand. In Table 2, the final demand effect is decomposed into these two components.

Box 2: Components of employment growth

We decompose employment growth into three components: labor productivity, business practices, and final demand. Our methodology is a straightforward extension of standard input-output analysis.

Denote the ratio of labor per unit of output as a vector μ, where each element corresponds to a single-digit (SIC) sector. Let $\hat{\mu}$ be a diagonal matrix with μ on the principal diagonal. Let Y denote the vector of final demand. Then, the employment vector E_1 can be determined as:

$$E_1 = \hat{\mu}_1 B_1 Y_1$$

Next, denote changes from period 1 to period 2 as Δ, and let subscripts denote periods 1 and 2. Then, employment in period 2, E_2, can be decomposed as follows:

$$E_2 = \hat{\mu}_1 B_1 Y_1 + \Delta\hat{\mu} B_1 Y_1 + \hat{\mu}_2 \Delta B\, Y_2 + \hat{\mu}_2 B_1 \Delta Y$$

The first term, $\hat{\mu}_1 B_1 Y_1$, is employment in period 1. The second term, $\Delta\hat{\mu} B_1 Y_1$, denotes employment change from period 1 to period 2 caused by changes in labor productivity. The third term, $\hat{\mu}_2 \Delta B\, Y_2$, represents employment change caused by changing business practices. The last term, $\hat{\mu}_2 B_1 \Delta Y$, represents employment change caused by changes in final demand. All elements of equation (2) are in vector form.

Our next step is to decompose the last term of equation 2, employment change due to changing final demand ($\hat{\mu}_2 B_1 \Delta Y$), into two additional terms: a) employment change due to a change in the composition of final demand, and b) employment change due to a change in the size of final demand

$$\begin{aligned} E_2 &= \hat{\mu}_1 B_1 Y_1 + \Delta\hat{\mu} B_1 Y_1 + \hat{\mu}_2 \Delta B Y_2 + \hat{\mu}_2 B_1 \Delta Y \\ &= \hat{\mu}_1 B_1 Y_1 + \Delta\hat{\mu} B_1 Y_1 + \hat{\mu}_2 \Delta B Y_2 + \hat{\mu}_2 B_1 (Y_2 - Y_1) \\ &= \hat{\mu}_1 B_1 Y_1 + \Delta\hat{\mu} B_1 Y_1 + \hat{\mu}_2 \Delta B Y_2 + [\hat{\mu}_2 B_1 \{(Y_2 - rY_1) + (rY_1 - Y_1)\}] \\ &= \hat{\mu}_1 B_1 Y_1 + \Delta\hat{\mu} B_1 Y_1 + \hat{\mu}_2 \Delta B Y_2 + \hat{\mu}_2 B_1 \Delta Y_c + \hat{\mu}_2 B_1 \Delta Y_s \end{aligned}$$

where $r = (1^T Y_2)/(1^T Y_1)$ (r represents the ratio of final demand in period 2 to final demand in period 1).

The last row of Table 2 shows that at the aggregate economic level, virtually all the growth in employment due to the final demand effect was the result of an increase in the size of the economy. Within the aggregate economy, however, the manufacturing and service sectors displayed considerably different behavior. Changes in final demand led to a small rise (0.6 percent) in manufacturing employment. But behind this small number lay considerable activity, with a growing economy tugging manufacturing employment in one direction, and changes in final demand composition tugging in another. Manufacturing employment grew by 3.2 percent as a result of increased final demand caused by a growing economy. Nearly two-thirds of this gain of 3.2 percent took place in the durable manufacturing sector. Over the same period, changes in the composition of final demand reduced manufacturing employment by 2.6 percent. Almost all this 2.6 percent decline in manufacturing employment took place in the durable manufacturing sector. Thus, changes in final demand had much larger effects on employment in durable manufacturing than initially appeared.

As shown in Table 1, total employment in the personal and business service sector grew by about 8.5 percent from period 1 to period 2. Of that 8.5 percent, 1.7 percent was the result of changing business practices, 0.3 percent caused by changes in labor productivity, and 6.5 percent caused by changes in final demand. Table 2 decomposes this 6.5 percent increase into size and composition effects. A growing economy leading to increased final demand caused personal and business service employment to grow by 3 percent. The remaining 3.5 percent was due to changes in the composition of final demand. In summary, changes in the composition of final demand caused manufacturing employment to fall by 2.6 percent and personal and business service employment to rise by 3.5 percent.

These results indicate that for the personal and business service industry, changes in final demand were far more significant than changes in business practices. In particular, changes in the economy affected the personal and business service sector primarily through changing final demand, rather than through changing business practices. If the unbundling hypothesis were true, we would have expected the increase in service employment to be explained primarily by changes in business practices. Thus, our results in Tables 1 and 2 cast serious doubts upon the unbundling hypothesis.

Conclusions

In this article, we examined the Chicago metropolitan economy in an attempt to understand the patterns underlying employment growth. On the surface, employment growth was modest, averaging 7.6 percent from the period of 1972-79 to the period of 1980-87. We analyzed aggregate growth in two ways. First, we looked at individual sectors of the economy, in an attempt to answer the question: which industries were responsible for the employment growth? In investigating this issue, we found a striking pattern. The economy-wide employment growth of 7.6 percent was caused by a dramatic increase in service sector employment, which more than compensated for the decline in the manufacturing sector's employment.

Second we looked at causal factors underlying this sectorial change in an attempt to answer the question: what factors caused these changes? We focused on three causal factors of employment growth: changes in labor productivity, changes in business practices and changes in final demand. We further disaggregated final demand effects into size and composition effects. Advances in labor productivity led to a decline of nearly 4 percent in economy-wide employment, while changes in final demand resulted in an increase of nearly 11 percent in economy-wide employment. On an aggregate level, almost all the change in employment due to changing final demand resulted from a growing economy. The story was much more complicated at the sectorial level. Our results confirmed our hypothesis that, at the sectorial level, changes in the composition of final demand exerted considerable influence on employment changes in Chicago.

Advances in manufacturing labor productivity and changing business practices decreased manufacturing employment, while changes in final demand had little effect on aggregate manufacturing employment.

The most striking impact on Chicago's aggregate employment resulted from changes in final demand for personal and business service sector goods. The impact of these changes on aggregate employment growth was nearly four times as strong as the impact caused by changing business practices. This dramatic growth in employment was the result of both a growing economy as well as a substantial change in the composition of final demand. These results strongly suggest that changes in final demand were the primary cause of significant employment growth in the services sector. This was true in spite of the fact that manufacturing generates more indirect jobs per direct job than the service sector. Recent results indicate that the Chicago manufacturing employment multiplier may be nearly twice as high as the Chicago service employment multiplier. Nevertheless, our findings suggest that advances in manufacturing productivity together with changing business practices mean that it is even less likely that manufacturing will be an important source of new jobs. In Chicago, we would expect that a large proportion of employment growth is likely to originate from the service sector, caused primarily by changes in the final demand for service sector goods. It is unlikely that this outlook could be changed by public policy.

We must qualify our conclusions with the following observations. Our analysis discusses unbundling only within the six county Chicago metropolitan area. It does not account for the possibility of, say, a Big Three automobile manufacturer in Detroit closing down its accounting department and hiring a Chicago-based accounting firm to manage its accounts. We are working towards developing a consistent set of multi-regional models similar to CREIM, for the Seventh District states. When those models are completed, we will be in a position to address such issues. Also, just as the United States is not a homogeneous country, the Seventh District states themselves display substantial differences in structure. Thus, one should exercise caution in extending the results presented in this article to other metropolitan areas. Finally, in order to fully understand the changing structure of Chicago's economy, we need to look at the changes in occupations across industries. Current research at REAL is focused in that direction, and we hope to present those results in future articles.

Can the above findings be generalized? In other words, should other regions and cities focus more on the final demand aspect of the service sector and pay less attention to the manufacturing sector? Based upon historical evidence, it is reasonable to assume that growth in the service sector has proceeded, and is likely to proceed, independently of growth in manufacturing in other regions. It is also reasonable to assume that improvements in manufacturing labor productivity, as well as changes in manufacturing business practices, are fairly widespread throughout the economy and not restricted to Chicago alone. Thus, future employment growth is less likely to come from manufacturing in other regions as well as in Chicago. Whether other regions should pay more attention to the service sector and particularly to final demand effects cannot be determined based on our results in this article because regional economies differ.

FOOTNOTES

[1]See Allardice (1990) for a description of REAL.

[2]See Kutscher (1988) and Tschetter (1987) for recent work on this subject.

[3]Much of this work has been conducted at the Bureau of Labor Statistics by Kutscher (1988), Tschetter (1987) and others.

[4]Using the Standard Industrial Classification—SIC—codes, we define the resources and construction sector as SICs 0 and 1, the manufacturing sector as SICs 2 and 3, and the services sector as SICs 4-8, with the TCU sector as SIC 4, Trade as SIC 5, FIRE as SIC 6, and personal and business services as SICs 7 and 8.

[5]For additional examples, see Kutscher (1988).

[6]For details regarding input-output tables and models, see Hewings (1985), or, for a more technical presentation, Miller and Blair (1985).

[7]The only exception that we are aware of for the United States are the Washington input-output tables. See Bourque (1987).

[8]CREIM is based upon the Washington Projection and Simulation Model (WPSM). For details, see Conway (1990).

[9]Details are reported in Hewings and Israilevich (forthcoming).

REFERENCES

Allardice, David R., "Chicago Fed and University of Illinois form regional research lab," *Economic Perspectives*, 14, Federal Reserve Bank of Chicago, March/April, 1990, pp. 13-14.

Bourque, P.J., "The Washington state input-output study for 1982," Seattle: Graduate school of business administration, University of Washington, 1982.

Conway, R.S., "The Washington Projection and Simulation Model: ten years of experience with a regional interindustry econometric model," *International Regional Science Review*, Spring, 1990.

Duchin, F., "Role of services in the U.S. economy," in *Technology in services: policies for growth, trade, and employment*, Guile, B.R. and J.B. Quinn, National Academy Press, Washington D.C., 1988, pp. 76-98.

Hewings, G.J.D., *Regional input-output analysis*, Scientific Geography Series, 9, Sage Publications, Beverly Hills, CA, 1985.

Hewings, G.J.D., and P.R. Israilevich, "Construction of the Chicago 1982 input-output table", *Regional Economic Issues*, Federal Reserve Bank of Chicago, forthcoming.

Hewings, G.J.D., P.R.Israilevich, and R. Mahidhara, "The structure of the Chicago economy," Mimeo, Regional Economics Applications Laboratory, Chicago, January, 1990.

Israilevich, P.R., and R. Mahidhara, "Chicago's economy: Twenty years of structural change," *Economic Perspectives*, 14, Federal Reserve Bank of Chicago, March/April 1990, pp. 15-23.

Kutscher, R.E. "Growth of service employment in the United States," in *Technology in services: Policies for growth, trade, and em-*

ployment, Guile, B.R. and J.B. Quinn eds., National Academy Press, Washington D.C., 1988, pp. 47-75.

Miller, R.E. and P.D. Blair, Input-output analysis: foundations and extensions, Prentice Hall, Englewood, NJ, 1985.

Tschetter, J. "Producer services industries: why are they growing so rapidly?" *Monthly Labor Review*, December, 1987, pp. 31-40.

The Great Lakes Economy

Looking North and South

A conference on the region's resources, economy, and development policies.

Detroit, Michigan, April 30, 1991

Sponsored by the Federal Reserve Bank of Chicago, The Council of Great Lakes Governors, and the Great Lakes Commission, the conference will be held at the Westin Hotel, Renaissance Center, in Detroit. The conference will serve as a forum for policymakers and the public to take stock of the region's economy—broadly defined to include both the U.S. and Canadian sides—and to discuss emerging challenges concerning economic development, public-private cooperation, and strategic planning. Drawing from a forthcoming book of the same title, speakers and participants will address issues covering the environment, natural resources, key industries, structural change in the economy, and the region's economic outlook.

If you would like to receive an invitation, or to learn more about the forthcoming book, please telephone (312) 322- 5111 or send your name and address to:
Public Information Center - 3rd floor
Federal Reserve Bank of Chicago
P.O.Box 834
Chicago, Illinois 60690-0834

Technology shocks and the business cycle

Martin Eichenbaum

Historically, much research in macroeconomics has focused on assessing the relative importance of different shocks to aggregate economic activity. The traditional view, shared by Monetarists and Keynesians alike, is that exogenous shocks to aggregate demand, such as those induced by shifts in monetary policy, are central impulses to the business cycle. Irrespective of their other differences, adherents of the traditional view share the common goal of striving to understand the mechanisms by which monetary policy affects aggregate economic activity.

The repeated oil shocks of the last 15 years and the accelerating pace of technological change have led to a breakdown in the consensus that changes in aggregate demand are the main sources of business cycles. The decline of the traditional view coincided with the development of a group of models, collectively known as Real Business Cycle (RBC) theories. In sharp contrast to the traditional view, RBC theories seek to explain the business cycle in ways that abstract from monetary considerations entirely. According to these theories, exogenous shocks to aggregate supply, such as technology shocks, are the critical source of impulses to postwar U.S. business cycles. While RBC theorists do not claim that monetary policy is inherently neutral, they do believe that RBC models can capture the salient features of postwar U.S. business cycles without incorporating monetary shocks into the analysis.

Pursuing such a strategy, Kydland and Prescott (1982) were able to construct and analyze a simple general equilibrium model of the U.S. economy in which technology shocks were apparently able to account for *all* output variability in the postwar U.S. Building on Kydland and Prescott's work, Hansen (1985) and other researchers showed that variants of the basic RBC model were also able to account for the relative volatility of key aggregate variables such as real consumption, investment, and per capita hours worked. Given these findings, the need for an adequate theory of monetary and fiscal sources of instability has come to seem much less pressing. Perhaps as a consequence, the amount of research devoted to these topics has declined precipitously.

Not surprisingly, RBC theories have generated a great deal of controversy. In part, this controversy revolves around the substantive claims made by RBC analysts. At the same time there has been considerable controversy about the fact that RBC analysts address the data using highly stylized, general equilibrium models.[1] Like all theoretical models, RBC models abstract from different aspects of real-

Martin Eichenbaum is professor of economics at Northwestern University and senior consultant at the Federal Reserve Bank of Chicago. The author thanks Craig Burnside, Lawrence Christiano, Sergio Rebelo, Thomas Sargent, and Mark Watson for their advice and help. This article is based upon "Real business cycle theory: wisdom or whimsy?," forthcoming, *Journal of Economic Dynamics and Control*.

ity. According to this criticism, all theoretical models, including RBC models, are wrong. While I agree that theoretical models are necessarily false, this criticism overlooks the real usefulness of many theoretical models. What is striking about RBC models is their apparent ability to account for important features of the business cycle, despite their obvious simplicity.

This article assesses the quality of the empirical evidence provided by RBC analysts to support their substantive claims regarding the cyclical role of technology shocks. I argue that the data and the methods used by these analysts are, in fact, almost completely uninformative about the role of technology shocks in generating aggregate fluctuations in U.S. output. In addition I argue that their conclusions are not robust either to changes in the sample period investigated or to small perturbations in their models. For these reasons, I conclude that the empirical results in the RBC literature do not constitute a convincing challenge to the traditional view regarding the cyclical importance of aggregate demand shocks.

The remainder of this article is organized as follows. The second section summarizes the evidence used by RBC analysts to support the claim that technology shocks account for most of the variability in aggregate U.S. output. I then argue that the empirical approach used by RBC analysts, commonly referred to as "calibration," does not provide useful input into the problem of deciding which impulses have been the major sources of postwar fluctuations in output. The third section analyzes the sensitivity of RBC conclusions to simple perturbations in the model as well as to changes in the sample period investigated. Finally, the fourth section contains some concluding remarks.

Technology shocks and aggregate output fluctuations

This section reviews the basic empirical results presented by RBC analysts to support their contention that aggregate technology shocks account for a large percentage of aggregate U.S. output fluctuations. In presenting these results I abandon the RBC analysts' counterfactual assumption that the value of the model's structural parameters are actually known, rather than estimated. I then show that the strong conclusions which mark the RBC literature depend critically on this assumption. Absent this crucial assumption, the sharp inferences which RBC analysts draw regarding the importance of technology shocks are not supported by the data. I conclude that although technology shocks almost certainly play some role in generating the business cycle, there is simply an enormous amount of uncertainty about just what percentage of aggregate fluctuations they actually do account for. The answer could be 70 percent as Kydland and Prescott (1989) claim, but it could also be 5 percent or even 200 percent.

A prototypical Real Business Cycle Model

RBC models share the view that aggregate economic time series correspond to the evolution of a dynamic stochastic equilibrium in which optimizing firms, labor suppliers, and consumers interact in stochastic environments. The basic sources of uncertainty in agents' environments constitute the impulses to the business cycle. The type of impulse which has received the most attention are shocks to the aggregate production technology which affect both the marginal productivity of labor and the marginal productivity of capital.

Under these circumstances the time series on hours worked and the return to working correspond to the intersection of a stochastic labor demand curve with a fixed labor supply curve.[2] As long as agents are willing to substitute labor over time, an increase in the time t marginal productivity of labor ought to generate an increase in per capita hours worked, real wages, and output. Given a temporary increase in aggregate output and a desire on agents' part to smooth consumption over time, these theories also predict a large positive increase in investment as well as a positive but smaller increase in consumption.

In order to assess the quantitative implications of RBC theories it is useful to focus our attention on one widely used RBC model—the Indivisible Labor Model associated with Gary Hansen (1985) and Richard Rogerson (1988). The basic setup of that model can be described as follows. The economy is populated by a finite number of infinitely lived, identical, perfectly competitive individuals. Each person is endowed with T units of time which can be allocated towards work or leisure. To go to work, a person must incur a fixed cost, ξ, denominated in terms of hours of foregone leisure. The length of the workday per se is some constant, say f hours, so that a working person has $(T-f-\xi)$ hours of leisure. An unemployed person has T hours of leisure. Individuals care about leisure and consumption at different points in time. Consequently, labor supply behavior depends on a number of factors. First, the typical individual cares about the current return to working versus taking leisure. In the typical model, a higher real wage rate today implies that more people wish to work today, that is, labor suppliers are willing to substitute consumption for leisure. Second, current labor supply also depends on the returns to working today versus the returns to working in the future. In the typical model this means that, in response to a temporarily high wage rate today, more people wish to work today, that is, labor suppliers are willing to engage in intertemporal substitution of leisure and consumption.

According to the model, perfectly competitive firms combine labor services and capital to produce a single storable good which is sold in competitive markets. The good can be consumed immediately or used as capital one period later. An important feature of the model is that firms' production technologies are subject to stochastic technology shocks. For example, a positive technology shock increases the marginal productivity of both capital and labor. Other things equal, such a shock would increase firms' demand for labor and capital. In the typical model, the technology shock is modeled as a stationary autoregressive process which displays positive serial correlation. This means that positive technology shocks are expected to persist over time, although not permanently. The assumption that technology shocks are not permanent is particularly important for the model's labor market implications. If the shocks were permanent, the marginal productivity of labor and the return to working would be permanently higher. Other things equal, this would choke off the incentive for labor suppliers to intertemporally substitute leisure in response to an increase in the return to working. The assumption that technology shocks are persistent is particularly important for the model's capital market implications. It takes time for capital investments to come to fruition. If the technology shocks were completely transitory, the demand for investment goods would be unaffected by technology shocks.

Finally, the model supposes that, like technology shocks, government purchases of goods and services evolve according to a stationary autoregressive process which displays positive serial correlation. This means that a positive shock to government purchases leads agents to expect unusually high levels of government consumption for some periods to come. The higher the present value of government consumption, the higher the perceived level of lump sum taxes faced by the typical individual. The resulting negative income effect translates into an increase in the aggregate supply of labor and therefore equilibrium employment and output.[3]

In sum, according to the model, agents face two kinds of uncertainty—the level of technology and the level of government purchases. Shocks to these variables are the sole sources of aggregate fluctuations. Positive shocks to either of these variables tend to induce increases in aggregate output. The resulting fluctuations in aggregate real variables are not purely transitory for two reasons. First, the presence of capital tends to induce serial correlation in the endogenous variables of the model. Second, the exogenous variables—the state of technology and the level of government—are assumed to be serially correlated over time. The reader is referred to the Box for the precise details of the model.

Quantitative implications of the theory

In reporting the model's quantitative implications I will make use of constructs known as "moments". These refer to certain characteristics of the data generating process, such as a mean or a variance. Moments are classified according to their order. An nth order moment refers to the expected value of an nth order polynomial function of the variables in question. An example of a first order moment would be the unconditional expected value of time t output, Ey_t. Examples of second order moments of the output process are the unconditional variance of y_t, $E[y_t-Ey_t]^2$, and the covariance between output at time t and time $t-\tau$, $E[y-Ey_t][y_{t-\tau}-Ey_{t-\tau}]$. An example of a second order moment involving two variables would be the covariance between time t output and time t hours worked, $E[y_t-Ey_t][n_t-En_t]$.

Suppose that we denote the model's structural parameters by the vector Ψ. Given a particular value for Ψ, it is straightforward to deduce the model's implications for a wide variety of moments which might be of interest. In practice RBC analysts have concentrated on their models' properties for a small set of moments which they argue describe the salient features of the business cycle. The moment which has received the most attention is the standard deviation of output, σ_y.[4] RBC analysts also report their models' implications for objects like the standard deviations of consumption, investment, average productivity, and hours worked. While this list of moments is by no means exhaustive, it is primarily on these dimensions of the data that RBC analysts have claimed their major successes.

To quantify whether a model has succeeded in accounting for some moment, RBC studies condition their empirical analysis on a particular value for Ψ, say $\hat{\Psi}$. The model's prediction for some moment is then compared to an estimate of the corresponding data moment. The ratio between these two magnitudes is referred to as the percent of the moment in question for which the model accounts. For example, consider the variance of output. When RBC analysts say that the model accounts for 100λ percent of the variance of output, what they mean is that, for this moment, their model yields λ equal to

(1) $\lambda = \hat{\sigma}^2_{ym}(\hat{\Psi})/\hat{\sigma}^2_{yd}$.

Here the numerator denotes the variance of model output, calculated under the assumption that Ψ is equal to $\hat{\Psi}$, and the denominator denotes an estimate of the variance of actual U.S. output. The claim that technology shocks account for most of the fluctuations in postwar U.S. output corresponds to the claim that λ is a large number, with the current estimate being between .75 and 1.0, depending on exactly which RBC model is used.[5]

To evaluate these types of claims we abstract for the moment from issues like sensitivity to perturbations in the theory or changes in the sample period being considered. As decision makers, we need to know how much confidence to place in statements like "The model accounts for λ percent of the variability of output." But to answer this question we need to know how sensitive λ is to small perturbations in $\hat{\Psi}$. And in order to answer this question we must decide on what a small perturbation in $\hat{\Psi}$ is.

Unfortunately, the existing RBC literature does not offer much help in answering these questions. This is because RBC analysts have not used formal econometric methods, either at the stage when model parameter values are selected, or at the stage when the fully parameterized model is compared to the data. Instead they use a variety of informal techniques, known as "calibration." Unfortunately, for diagnostic purposes, these techniques are not a satisfactory alternative to formal econometric methods. This is because objects like λ are random variables, and hence are subject to sample uncertainty. Calibration techniques ignore the sample uncertainty inherent in such statistics. As a result, the calibrator must remain mute in response to the question "How much confidence do we have that the model accounts for 100λ percent of the variance of output?"

That there is sampling uncertainty in random variables like λ follows from the fact that they are statistics in the sense defined by Prescott (1986), that is, they are real valued functions of the data. In the case of λ, the precise form of that dependency is determined jointly by the functions defining $\hat{\sigma}^2_{yd}$, $\hat{\Psi}$, and $\sigma^2_{ym}(\hat{\Psi})$. According to Equation (1), sampling uncertainty in any of these random variables implies the existence of sampling uncertainty in λ. In fact, *all* of these objects are random variables, subject to sampling uncertainty. To see this, consider first $\hat{\sigma}^2_{yd}$. We do not know the true variance of U.S. output, σ^2_{yd}. This a population moment which must be estimated via some well defined function of the data. Since $\hat{\sigma}^2_{yd}$ is an estimate of σ^2_{yd}, it is a random variable, subject to sampling uncertainty. Next consider, the vector $\hat{\Psi}$, the *estimated* value of the model's structural parameters. It too is a random variable subject to sampling uncertainty. To see this, consider an element of Ψ like α, a parameter that governs the marginal physical productivity of labor. Calibrators typically choose a value for α, say $\hat{\alpha}$, which implies that the model reproduces the "observed" share of labor in national income. But we do not observe the population value of labor share in national income; this is an object which must be estimated via some function of the data. Since the estimator defined by that function is

The Indivisible Labor Model: a prototypical Real Business Cycle Model

The representative individual's time t utility level depends on time t consumption, c_t, and time t leisure, l_t, in a way described by the function

(1) $U(c_t, l_t) = u(c_t) + v(l_t)$.

The functions u and v are strictly increasing, concave functions of consumption and leisure, respectively. At time zero, the typical individual seeks to maximize the expected discounted value of his/her lifetime utility, that is,

(2) $E_0 \sum_{t=0}^{\infty} \beta^t U(c_t, l_t)$,

where E_0 denotes the expectations operator conditional on the typical person's time zero information set and β is a subjective discount rate between zero and one.

The single consumption good in this economy is produced by perfectly competitive firms using a constant returns to scale technology, $F(k_t, n_t, z_t)$, which relates the beginning of time t capital, k_t, total hours worked, n_t, and the time t stochastic level of technology, z_t, to total output. The stock of capital evolves according to

(3) $k_{t+1} = (1-\delta)k_t + i_t$

where i_t denotes time t gross investment and δ is the constant depreciation rate on capital, $0 < \delta < 1$.

In the aggregate, consumption plus gross investment plus government purchases of the good cannot exceed current output, that is the economy is subject to the aggregate budget constraint,

(4) $c_t + k_{t+1} - (1-\delta)k_t + x_t \leq y_t$.

The variable x_t denotes time t government purchases of the goods.

To derive the quantitative implications of the preceding model we must specify the functions summarizing preferences and technology, u, v, and F, as well as the laws of motion governing the evolution of the technology shocks and government purchases. In addition we must be specific about the market setting in which private agents interact. As in most existing RBC studies, we suppose that households and firms interact in perfectly competitive markets. As it turns out, deriving the competitive equilibrium of our model is greatly simplified if we exploit the well-known connection between competitive equilibria and optimal allocations. This connection allows us to analyze a simple "social planning" problem whose solution happens to coincide with the competitive equilibrium of our economy.

In displaying the planning problem which is appropriate for our economy it is useful to first make explicit Hansen's assumptions regarding preferences and technology. The function $u(c_t)$ is assumed to be given by $ln(c_t)$. Total time t output, y_t, is assumed to be produced using the production

---

subject to sampling uncertainty, so too is $\hat{\Psi}$. It follows that $\sigma^2_{ym}(\hat{\Psi})$, which depends on $\hat{\Psi}$, is also a random variable, subject to sampling uncertainty.

The previous discussion indicates that all of the elements required to calculate λ are random variables. Clearly λ will inherit the randomness and sampling uncertainty in its constituent elements. Since calibration techniques treat the elements of λ ($\hat{\sigma}^2_{yd}$, $\hat{\Psi}$, and $\sigma^2_{ym}(\hat{\Psi})$) as fixed numbers, these techniques must also treat λ as a fixed number rather than as a random variable. As a consequence, calibration techniques cannot be used to quantify the sampling uncertainty inherent in an object like λ. To do this, one must use formal econometric methods.

In recent work, Lawrence Christiano and I discuss one way to quantify sampling uncertainty in the diagnostic statistics typically used by RBC analysts.[6] The basic idea is to utilize a version of Hansen's (1982) Generalized Method of Moments procedure in which the estimation criterion is set up so that, in effect, the estimated parameter values succeed in equating model and sample first order moments of the data. It turns out that these values are very similar to the values employed in existing RBC studies. For example, most RBC studies assume that the quarterly depreciation rate, δ, and the share of capital in the aggregate production function, $(1-\alpha)$, equal .025 and .36, respectively.[7] Our procedure yields point estimates of .021 and .35, respectively.

function $F(k_t, n_t, z_t) = z_t k_t^{1-\alpha} n_t^{\alpha}$. The technology shock, z_t, evolves according to

$$(5)\quad z_t = \gamma^t A_t$$
$$A_t = A_{t-1}^{\rho_a} \exp(\epsilon_{t-1}).$$

Here A_t is the stationary component of z_t, ρ_a is a scalar satisfying $|\rho_a| < 1$, ϵ_t is the time t innovation to $ln(A_t)$ with mean ϵ and standard deviation σ_ϵ. The parameter γ is a positive constant which governs growth in the economy.[1] In addition government purchases are assumed to evolve according to

$$(6)\quad x_t = \gamma^t g_t$$
$$g_t = g_{t-1}^{\rho_g} \exp(\mu_t).$$

Here g_t is the stationary stochastic component of x_t, ρ_g is a scalar satisfying $|\rho_g| < 1$, and μ_t is the innovation in $ln(g_t)$ with mean μ and standard deviation σ_μ.

Proceeding as in Hansen (1985) and Rogerson (1988) it can be shown that the competitive equilibrium laws of motion for k_t, c_t, and n_t, correspond to the solution of a planning problem in which streams of consumption services and hours worked are ranked according to the criterion function:

$$(7)\quad E_0 \sum_{t=0}^{\infty} \beta^t \{\ln(c_t) + \theta(T-n_t)\}$$

where θ is some positive scalar. The planner maximizes (7) subject to the resource constraint

$$(8)\quad c_t + k_{t+1} - (1-\delta)k_t + x_t = z_t k_t^{1-\alpha} n_t^{\alpha},$$

and the laws of motion for z_t and x_t given by (5) and (6).

There are at least two interpretations of the term involving leisure in (7). First, it may just reflect the assumption that the function $v(l_t)$ is linear in leisure. The second interpretation builds on the assumption that there are fixed costs of going to work. Because of this individuals will either work some fixed positive number of hours or not at all. Assuming that agents' utility functions are separable across consumption and leisure, Rogerson (1988) shows that a market structure in which individuals choose the probability of being employed rather than actual hours worked will support the Pareto optimal allocation. With this interpretation, equation (7) represents a reduced form preference ordering which can be used to derive the competitive equilibrium allocation. However, at the micro level of the individual agent, the parameter θ places no restrictions on the elasticity of labor supply.

[1] Our model exhibits balanced growth, so that the log of all real variables, excluding per capita hours worked, have an unconditional growth rate of γ.

The key difference between the procedures does not lie so much in the point estimates of Ψ. Rather the difference is that, by using formal econometrics, our procedure allows us to translate sampling uncertainty about the functions of the data which define our estimator of Ψ into sampling uncertainty regarding $\hat{\Psi}$ itself. This information leads to a natural definition of what a small perturbation in $\hat{\Psi}$ is. In turn this makes it possible to quantify uncertainty about the model's moment implications.

Before reporting the results of implementing this procedure for the Indivisible Labor Model, I must digress for one moment and discuss the way in which growth is handled. In practice empirical measures of objects like y_t display marked trends, so that some stationary inducing transformation of the data must be adopted. A variety of alternatives are available to the analyst. For example, our setup implies that the data are realizations of a trend stationary process, with the log of all real variables (excluding per capita hours worked) growing as a linear function of time. So one possibility would be to detrend the time series emerging from the model as well as the actual data assuming a linear time trend and calculate the moments of the linearly detrended series.

A different procedure involves detrending model time series and the data using the filter discussed in Hodrick and Prescott (1980). Although our point estimates of Ψ were not obtained using transformed data, diagnostic second moment results were generated using this transformation of model time series and U.S. data.

I do this for three reasons. First, many authors in the RBC literature report results based on the Hodrick Prescott (HP) filter.[8] In order to evaluate their claims, it seems desirable to minimize the differences between our procedures. Second, the HP filter is in fact a stationary inducing transformation for trend stationary processes.[9] So there is nothing logically wrong with using HP transformed data. Using it just amounts to the assertion that you find a particular set of second moments interesting as diagnostic devices. And third, all of the calculations reported in this article were also done with linearly detrended data as well as growth rates. The qualitative results are very similar, while the quantitative results provide even stronger evidence in favor of the points I wish to make. So presenting results based on the HP filter seems like an appropriate conservative reporting strategy.

Volatility and the Indivisible Labor Model

Using aggregate U.S. time series data covering the period 1955:3-1984:4, Burnside, Eichenbaum, and Rebelo (1990) estimated the Indivisible Labor Model discussed in the Box and implemented the diagnostic procedures developed in Christiano and Eichenbaum (1990). A subset of our results are reproduced in Table 1. The third column summarizes the Indivisible Labor Model's implications for the standard deviation of hours worked, σ_n, the volatility of consumption, investment, and government purchases relative to output, σ_c/σ_y, σ_i/σ_y, and σ_g/σ_y, respectively, as well as the volatility of hours worked relative to productivity, σ_n/σ_{APL}. The second column of this table reports their estimates of the corresponding U.S. data moments. The column labeled "Indivisible Labor Model" contains three numbers for each moment. The top number is the model's point prediction for each moment. These were calculated using the point estimates of Ψ obtained by Burnside, Eichenbaum, and Rebelo (1990).[10] The middle number is the estimated standard error of the first number, and reflects sampling uncertainty in $\hat{\Psi}$. For each moment we also tested the null hypothesis that the model moment equals the population moment. The bottom number equals the probability value of the Chi-square statistic discussed in Christiano and Eichenbaum (forthcoming) for testing such hypotheses.

TABLE 1

Indivisible Labor Model—selected second moments

Second moment	Whole sample*: U.S. data**	Whole sample*: Indivisible Labor Model***
σ_c/σ_y	.44 (.03)	.53 (.24) [.69]
σ_i/σ_y	2.22 (.07)	2.65 (.59) [.47]
σ_g/σ_y	1.15 (.20)	1.09 (.35) [.89]
σ_n/σ_{APL}	1.22 (.12)	1.053 (.46) [.72]
σ_n	.017 (.002)	.013 (.005) [.94]

SOURCE; C. Burnside, M. Eichenbaum, and S. Rebelo, "Labor hoarding and the business cycle," manuscript, Northwestern University.

*Whole sample corresponds to the sample period 1955:3-1984:4.

**Numbers in parentheses correspond to standard errors.

***Numbers in brackets refer to the probability value of the test statistic used by Burnside, Eichenbaum, and Rebelo (1990) to test whether a model and data moment are the same in population.

Table 1 shows that the Indivisible Labor Model does well in accounting for the volatility of consumption, investment, and government purchases relative to output, as well as the volatility of hours worked, both in absolute terms and relative to the volatility of productivity. In particular one cannot reject, at conventional significance levels, the null hypotheses that the model values of σ_n, σ_c/σ_y, σ_i/σ_y, σ_g/σ_y, and σ_n/σ_{APL} are equal to the corresponding data population moments.

Technology shocks and aggregate fluctuations in the Indivisible Labor Model

Table 2 reports a subset of our results for the Indivisible Labor Model which pertain to the question of what percentage of aggregate fluctuations are accounted for by technology shocks. The first row corresponds to the model in which there are shocks to technology

TABLE 2

Indivisible Labor Model—variability of output

	Whole sample*			
	σ_ϵ**	ρ_a	σ_{ym}	λ
Indivisible Labor Model (variable government)	.0089 (.0013)	.986 (.026)	.017 (.007)	.82 (.64)
Indivisible Labor Model (constant government)	.0089 (.0013)	.986 (.026)	.017 (.007)	.78 (.64)

SOURCE: C. Burnside, M. Eichenbaum, and S. Rebelo, "Labor hoarding and the business cycle," manuscript, Northwestern University.

*Whole sample corresponds to the sample period 1955:3-1984:4.

**Numbers in parentheses correspond to standard errors.

as well as to government purchases. The second row corresponds to the model in which the only shocks to agents' environments are stochastic shifts in the aggregate production technology. Numbers in parentheses denote the standard errors of the corresponding statistics. All uncertainty in the model statistics reflects uncertainty regarding the values of the structural parameters only.[11]

Four key features of these results deserve comment. First, the standard errors associated with our point estimates of the parameter governing serial correlation in the technology shock, ρ_a, are quite large. This is important because the implications of RBC models are known to be sensitive to changes in this parameter, especially in a neighborhood of ρ_a equal to one.[12] Second, the standard errors on our estimate of the standard deviation of the innovation to the technology shock, σ_ϵ, are quite large. Evidently, there is substantial uncertainty regarding the population values of the parameters governing the evolution of the technology shocks. Third, incorporating government purchases into the model increases the value of λ only slightly from 78 percent to 82 percent.[13] Fourth, the fact that λ equals 78 percent when the only shocks are to technology appears to be consistent with claims that technology shocks explain a large percentage of the variability in postwar U.S. output.[14] Notice however that the standard error of λ is very large. There is a great deal of uncertainty regarding what percent of the variability of output the model accounts for. As it turns out, this uncertainty reflects uncertainty regarding ρ_a and σ_ϵ almost exclusively. Uncertainty regarding the values of the other parameters of the model has a negligible effect.[15]

Figure 1 presents a graphical depiction of the Indivisible Labor Model's implications for λ. Each point on the graph is generated by fixing λ at a specific value, λ^*, and then testing the hypothesis that $\sigma^2_{ym} = \lambda^*\sigma^2_{yd}$. The vertical axis reports the probability value of our test statistic for the corresponding value of λ. According to Figure 1, the Indivisible Labor Model may account for as little as 5 percent or as much as 200 percent of the variation in per capita U.S. output, in the sense that neither of these hypotheses can be rejected at conventional significance levels. It follows that, with this data set, the Indivisible Labor Model is almost completely uninformative about the role of technology shocks in generating fluctuations in U.S. output.[16] In particular, one cannot conclude on the basis of these results either that technology shocks were the primary shocks to aggregate output or that technology shocks played virtually no role in generating fluctuations in aggregate output. Any inference about the cyclical role of technology shocks in the postwar U.S. based solely on the point estimate of λ is unjustifiable.

Sensitivity of results to perturbations in the model

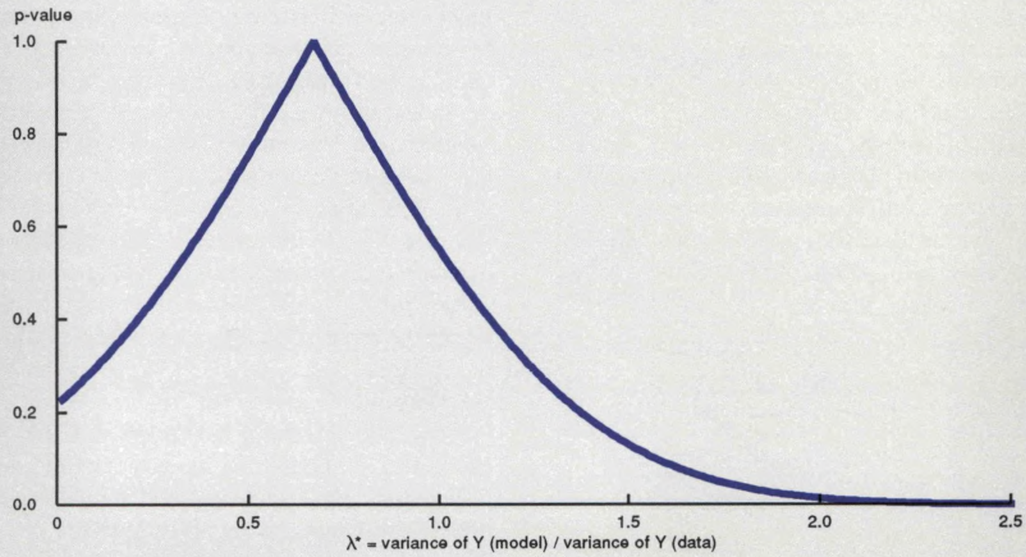
In the previous section I analyzed how accurately λ could be measured from the vantage point of a specific RBC model. In this section I investigate how sensitive the point estimate of λ itself is to small perturbations in the model. I begin by discussing the impact of labor hoarding and sample period selection on the empirical performance of the Indivisible Labor Model.

Incorporating labor hoarding into the Indivisible Labor Model

In order to demonstrate the fragility of λ to small perturbations in the theory, this section incorporates a particular variant of labor hoarding into the Indivisible Labor Model. The general notion of labor hoarding refers to behavior associated with the fact that firms do not always use their labor force to full capac-

FIGURE 1

Indivisible Labor Model (constant government)



ity. Given the costs of hiring and firing employees, firms may find it optimal to vary the intensity with which their labor force is used, rather than change the number of employees in response to transient changes in business conditions.

Existing RBC models, including the Indivisible Labor Model discussed in the second section, interpret virtually all movements in measured average productivity of labor as being the result of technology shocks. This is the rationale given by authors like Prescott (1986) for using the Solow residual as a measure of exogenous technology shocks. In practice, RBC analysts measure the Solow residual as that component of output which cannot be explained by the stock of capital and hours worked, given the assumed form for the aggregate production technology. Given our functional form assumptions, the time t value of the Solow residual, z_t, equals $y_t/(k_t^{1-\alpha} n_t^{\alpha})$. Various authors, ranging from Lucas (1989) to Summers (1986), have questioned this rationale by conjecturing that many of the movements in the Solow residual which are labelled as technology shocks are actually caused by labor hoarding. To the extent that this is true, empirical work which identifies technology shocks with the Solow residual will systematically overstate their importance to the business cycle.

Hall (1988), among others, has argued that if Solow residuals represent good measures of exogenous technology shocks, then under perfect competition, they ought to be uncorrelated with different measures of fiscal and monetary policy. In fact they are not. Evans (1990) has shown that the Solow residuals are highly correlated with different measures of the money supply. And Hall (1988) himself presents evidence they are also correlated with the growth rate of military expenditures.

In ongoing research, Craig Burnside, Sergio Rebelo, and I have tried to assess the sensitivity of inference based on Solow residual accounting to the Lucas/Summers critique. The model that we use incorporates a particular type of labor hoarding into a perfect competition, complete markets RBC model. The purpose of this Labor Hoarding Model is twofold. First, we use that model to assess the extent to which movements in the Solow residual can be explained as artifacts of labor hoarding type behavior. Second, we use the model to investigate the fragility of existing RBC findings with respect to the possibility that firms engage in labor hoarding behavior. Our basic findings can be summarized as follows:

(I) Labor hoarding with perfect competition and complete markets accounts for the observed correlation between government consumption and the Solow residual.

(II) Incorporating labor hoarding into the analysis substantially enhances the model's overall empirical performance. This improvement is particularly marked with respect to three important qualitative features of the joint behavior of average productivity and hours worked. First, average productivity and hours worked do not display any marked contemporaneous correlation. Second, average productivity leads the cycle in the sense that it is positively correlated with future hours worked. Third, average productivity is negatively correlated with lagged hours.[17]

(III) We conclude that RBC models are quite sensitive to the possibility of labor hoarding. Allowing for such behavior reduces our estimate of the variance of technology shocks by roughly 60 percent. Depending on the sample period investigated, this reduces the ability of technology shocks to account for aggregate output fluctuations by 30 to 60 percent.

The basic setup used by Burnside, Eichenbaum, and Rebelo (1990) to generate these conclusions can be described as follows. As in the Indivisible Labor Model of the second section there is a fixed cost, ξ, of going to work. As before the length of the work day equals f hours. Consequently the time t criterion of an employed person is given by

$$(2)\quad \ln(c_t) + \theta\ln(T-\xi-e_t f).$$

Here c_t denotes time t consumption, the parameter θ is a positive constant, and e_t denotes the level of time t effort. The time t criterion function of an unemployed person is just

$$(3)\quad \ln(c_t) + \theta\ln(T).$$

The aggregate production technology is now given by

$$(4)\quad y_t = A_t\, k_t^{1-\alpha}(\gamma^t N_t e_t f)^{\alpha}.$$

Here N_t denotes the total number of bodies going to work at time t and k_t denotes the stock of capital at the beginning of time t. The random variable A_t denotes the time t technology shock while γ is a positive constant which governs growth in the economy. See the Box for a description of the way in which A_t evolves over time.

What does the competitive equilibrium of this model look like? Since agents' criterion functions are separable across consumption and leisure, the consumption of employed and unemployed individuals will be the same in a competitive equilibrium. The problem whose solution yields the competitive equilibrium for this version of the model is given by

Maximize

$$(5)\quad E_0 \sum_{t=0}^{\infty} \beta^t\{\ln(c_t) + \theta N_t \ln(T-\xi-e_t f) + \theta(1-N_t)\ln(T)\}$$

subject to the aggregate resource constraint

$$(6)\quad A_t k_t^{1-\alpha}(\gamma^t N_t e_t f)^{\alpha} \geq c_t + x_t + k_{t+1} - (1-\delta)k_t.$$

In (6), the variable x_t denotes time t government purchases of goods. See the Box for a description of the law of motion for x_t.

If we assume that firms see the time t realization of the technology shock and government consumption *before* choosing employment and effort levels, N_t and e_t, then this model is observationally equivalent to the Indivisible Labor Model described in the Box. How can we perturb the model so as to capture labor hoarding behavior? A simple way to do this, without changing the nonstochastic steady state of the model, is to suppose that N_t must be chosen *before*, rather than *after*, time t government consumption and the level of technology is known. To provide a bound for the effects of labor hoarding in this setup, we maintain the assumption that the shift length, f, is constant.

The intuition underlying this perturbation is that it is costly for firms to vary the size of their work force. In the limit it is simply not feasible to change work force size in response to *every* bit of new information regarding the state of demand and technology. This notion is captured in the Labor Hoarding Model by assuming that firms make their employment decisions conditional on their views about the future state of demand and technology, and then adjust to shocks by changing labor effort. This adjustment is costly because workers care about *effective* hours of work.[18] More generally, incorporating unobserved time varying effort into the model can be thought of as capturing, in a rough manner, the type of measurement error induced by the fact that, in many industries, reported hours worked do not vary in a one to one way with actual hours worked. This explanation of procyclical productivity has been emphasized by various authors such as Fair (1969).

Suppose that an analyst computed the Solow residual using the formula $S_t = y_t/(k_t^{1-\alpha}n_t^{\alpha})$, where n_t is reported hours worked at time t. Burnside, Eichenbaum, and Rebelo (1990) show that, if labor effort is time varying, the Solow residual, the stationary component of the true technology shock, and effort, are, in equilibrium, tied together via the relationship

$$(7) \quad S_t^* = A_t^* + \alpha e_t^*.$$

Here the superscript * denotes the deviation of the natural log of a variable from its steady state value. The log linear equilibrium law of motion for e_t^*, the effort level, is of the form

$$(8) \quad e_t^* = \pi_1 k_t^* + \pi_2 N_t^* + \pi_3 A_t^* + \pi_4 g_t^*$$

where π_1, π_2, π_3, and π_4 are nonlinear functions of the structural parameters of the model.

Given Burnside, Eichenbaum, and Rebelo's point estimates of the model's structural parameters, both π_3 and π_4 are positive.[19] This implies that, other things equal, it is optimal to work harder when faced with a positive innovation in government purchases or technology, that is, *effort will be procyclical*. For example, Figure 2 presents the response of the Labor Hoarding Model to a 1 percent innovation in government consumption. By assumption, the number of people employed cannot immediately respond to this shock. However, effort rises by over 15 percent in the first period and then reverts to its steady state level. Panel (a) shows the implied movement in the Solow residual. Since effort has gone up in the first period but total hours of work have not changed, the Solow residual increases by about .10 percent. This is true *even though there has been no technology shock whatsoever*. As panel (d) shows, productivity rises in the first period by .1 percent in response to the 1 percent innovation in government consumption. Naive Solow residual accounting falsely interprets the increase in average productivity as arising from a shift in technology rather than an exogenous increase in government consumption.

Figure 3 shows how the Labor Hoarding Model responds to a 1 percent innovation in technology. Given agents' willingness to intertemporally substitute effective leisure over time, they respond to the shock in the first period by increasing effort by about .4 percent. As a result the Solow residual rises by 1.3 percent in response to the 1 percent technology shock. Again naive Solow residual accounting exaggerates the true magnitude of the technology shock. We conclude that naive Solow residual accounting systematically overestimates the level of technology in booms, systematically underestimates the level of technology in recessions, and systematically overestimates the variance of the true technology shock.

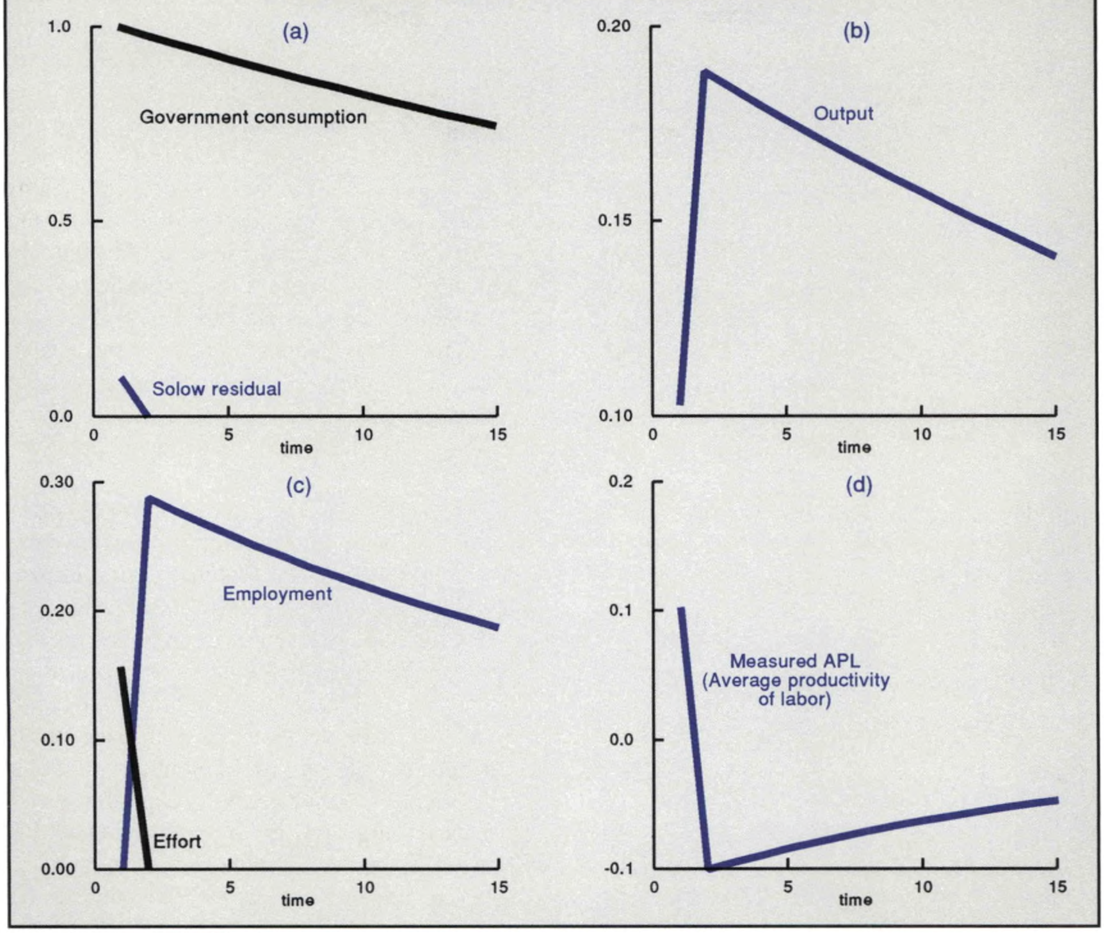
Note that our Labor Hoarding Model does not allow for variations in the degree to which capital is utilized. The fact that capital utilization rates vary in a procyclical manner has clear implications for the way in which movements in the Solow residual are interpreted. This is because the Solow residual is typically calculated under the assumption that the stock of capital is fully utilized. Under these circumstances, a change in the capital utilization rate would show up as an unexplained increase in output, that is, a change in the Solow residual. Since our Labor Hoarding Model does not allow for time varying capital utilization rates, it overstates the extent to which movements in the Solow residual are caused by exogenous technology shocks. Incorporating capital capacity utilization decisions into the model would presumably further reduce the cyclical role of technology shocks.[20]

Sample period sensitivity

Before discussing how incorporating labor hoarding into the model affects inference regarding λ we must first assess the impact of sample period selection on inference. Numerous researchers have documented the fact that the growth rate of average productivity slowed down substantially in the late 1960s. To document the likelihood of a break in the data, that is, a change in the unconditional growth of average productivity, Burnside, Eichebaum, and Rebelo (1990) performed a series of iterative Chow tests. Using these tests, we found that the null hypothesis of no break, that is, no change in the unconditional growth rate, is

FIGURE 2

Labor Hoarding Model—shock to government



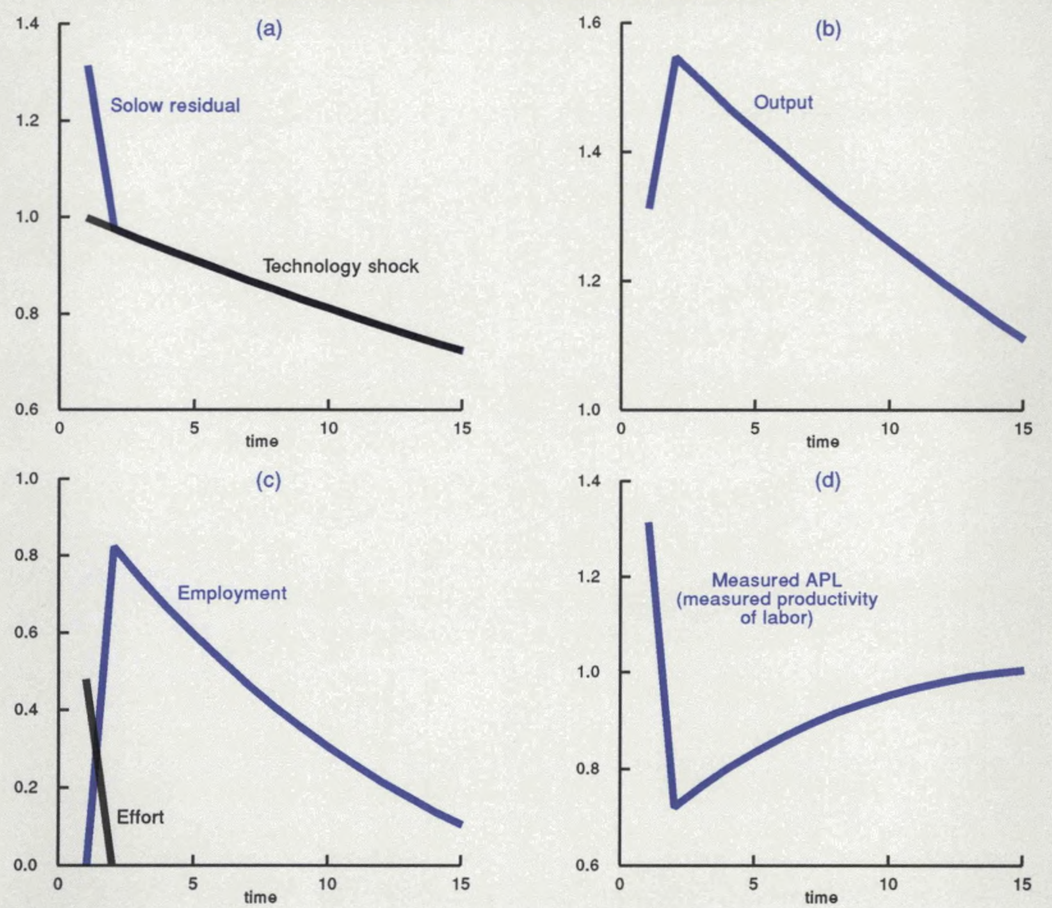
rejected at very high significance levels at all dates during the interval 1966:1-1974:2. The actual break point we chose was 1969:4, however, our results are not sensitive to the precise break point used.

In the same article we also discuss the impact of allowing for a break in the data on our estimates of the structural parameters. For both the Indivisible Labor Model and the Labor Hoarding Model, there are four important differences in the parameter values across the different sample periods. First, the estimated values of the unconditional growth rate of the Solow residual, in the first and second sample periods, .0069 and .0015 respectively, are quite different. Second, the estimated value of the coefficient governing serial correlation in the technology shock, ρ_a, is quite sensitive to a break in the sample period. For example, using the Indivisible Labor Model, the estimated value of ρ_a over the whole period (.986), is substantially larger than those obtained in the first (.86) and second (.88) sample periods. This is exactly what we would expect if there were indeed a break in the Solow residual process.[21] Third, estimates of σ_ϵ, the standard error of the innovation to technology, are also quite sensitive to the choice of sample period. The estimated value of σ_ϵ equals .0060, .0101, and .0089, in the first, second, and whole sample periods, respectively. Fourth, the estimates of γ_g (the growth rate in government consumption), ρ_g (the parameter which governs serial correlation in government purchases), and σ_μ (the standard error of the innovation to government purchases) are affected in the same qualitative way as the analog parameters governing the evolution of the Solow residual. However the quantitative differences are even larger.

These results have an important impact on the models' implications for some of standard

FIGURE 3

Labor Hoarding Model—shock to technology



diagnostic moments discussed in the second section. Table 3 reports the Labor Hoarding and Indivisible Labor Models' predictions for σ_n, σ_c/σ_y, σ_i/σ_y, σ_g/σ_y, and σ_n/σ_{APL} over the whole sample period. In addition that table reports our estimates of the corresponding data moments. Table 4 reports the corresponding results for the two subsample periods. Taken together, these tables substantiate our claim that the empirical performance of RBC models depends on sample period selection.

Recall that when the Indivisible Labor Model was estimated over the whole sample period, there was very little evidence against the model's implications for these moments. Table 3 shows that this is also true for the Labor Hoarding Model. Using the whole sample there is very little evidence against the individual hypotheses that the values of σ_n, σ_c/σ_y, σ_i/σ_y, σ_n/σ_{APL}, or σ_g/σ_y that emerge from either model are different from the corresponding data population moments. However, Table 4 indicates that the performance of both models deteriorates significantly when we allow for a break in the sample. This deterioration is quite pronounced with respect to the relative volatility of consumption and investment. Indeed using either sample period, and any conventional significance level, we can reject the hypotheses that these model moments equal the corresponding data population moments. Interestingly this result is not due to the fact that the data moment estimates change substantially. Rather, it is due to the fact that the models' implications for the two moments appear to be quite sensitive to a break in the sample. For example over the whole sample period, both models imply that consumption is roughly half as volatile as output. However, when estimated on the separate sample periods, both models predict that consumption is

TABLE 3

Indivisible Labor Model vs. Labor Hoarding Model—selected second moments

	Whole sample*		
Second moment	U.S. data**	Indivisible Labor Model***	Labor Hoarding Model
σ_c/σ_y	.44 (.03)	.53 (.24) [.69]	.48 (.19) [.80]
σ_i/σ_y	2.22 (.07)	2.65 (.59) [.47]	2.77 (.45) [.23]
σ_g/σ_y	1.15 (.20)	1.09 (.35) [.89]	1.29 (.15) [.50]
σ_n/σ_{APL}	1.22 (.12)	1.053 (.46) [.72]	1.017 (.41) [.39]
σ_n	.017 (.002)	.013 (.005) [.94]	.013 (.003) [.76]

SOURCE: C. Burnside, M. Eichenbaum, and S. Rebelo, "Labor hoarding and the business cycle," manuscript, Northwestern University.

*Whole sample corresponds to the sample period 1955:3-1984:4.

**Numbers in parentheses correspond to standard errors.

***Numbers in brackets refer to the probability value of the test statistic used by Burnside, Eichenbaum, and Rebelo (1990) to test whether a model and data moment are the same in population.

only a fourth as volatile as output.

The intuition behind this last result is straightforward. According to the permanent income hypothesis, an innovation to labor income causes households to revise their consumption by an amount equal to the annuity value of that innovation. If income was a first order autoregressive process that displayed positive serial correlation, then the annuity value of the innovation would be a strictly increasing function of the coefficient governing serial correlation in income. Using a model very similar to our Indivisible Labor Model, Christiano (1987) shows that the income effect of an innovation to the technology shock depends positively on the value of ρ_a, the parameter which governs the serial correlation of the technology shock. Since the point estimate of ρ_a falls in both subsamples, we would expect that, holding interest rates constant, the response of consumption to an innovation in the technology shock should also fall. Given that Christiano (1987) also shows that the impact of technology shocks on the interest rate in standard RBC models is quite small, it is not surprising that the model predicts lower values for σ_c/σ_y in the subsample periods. Since output equals consumption plus investment plus government consumption, and the latter does not respond to technology shocks, it follows that, other things equal, investment is more volatile because consumption is less volatile.

Labor hoarding and λ

Given the sensitivity of inference to sample period selection, we allow for a break in the data in reporting the impact of labor hoarding on λ. To begin with, consider the implications of allowing for time varying effort on the parameters governing the law of motion of technology shocks. Comparing Tables 5 and 6 we see that this change in the model leads to a large reduction in σ_ϵ. Based on the whole sample period, the variance (square of the standard error reported in the table) of the innovation to technology shocks drops by roughly 35 percent. In Sample period 1 and Sample period 2 this variance drops by 48 and 56 percent, respectively. Evidently, breaking the sample magnifies the sensitivity of estimates of σ_ϵ to time varying effort. A different way to assess this sensitivity is to consider the unconditional variance of the stationary component of the technology shock, σ_a^2, which equals $\sigma_\epsilon/(1-\rho_a^2)$. Allowing for time varying effort reduces the volatility of technology shocks by over 58 percent in the whole sample period, 49 percent in Sample period 1, and 57 percent in Sample period 2. These results provide support for the view that a large percentage of the movements in the observed Solow residual may be artifacts of labor hoarding type behavior.

How do these findings translate into changes regarding the model's implications for λ? Tables 5 and 6 indicate that over the whole sample period, introducing labor hoarding into the analysis causes λ to decline by 28 percent from .81 to .58. The sensitivity of λ is even more dramatic once we allow for a break in the sample. Labor hoarding reduces λ by 58 percent in the first sample period and by 63

TABLE 4

Indivisible Labor Model vs. Labor Hoarding Model—selected second moments: subsamples

	Sample period 1*			Sample period 2*		
Parameter	U.S. data**	Labor Hoarding Model***	Indivisible Labor Model	U.S. data	Labor Hoarding Model	Indivisible Labor Model
σ_c/σ_y	.49 (.08)	.27 (.03) [.009]	.24 (.05) [.02]	.42 (.03)	.23 (.05) [0.0]	.22 (.05) [.001]
σ_i/σ_y	2.085 (.17)	3.32 (.11) [0.0]	3.38 (.16) [0.0]	2.27 (.08)	3.41 (.17) [0.0]	3.42 (.18) [0.0]
σ_g/σ_y	2.20 (.42)	1.70 (.29) [.24]	1.10 (.43) [.10]	.55 (.08)	.76 (.10) [.04]	.46 (.09) [.51]
σ_n/σ_{APL}	1.009 (.16)	1.17 (.05) [.38]	1.85 (.70) [.27]	1.35 (.15)	1.21 (.05) [.40]	2.33 (.64) [.14]

Source: C. Burnside, M. Eichenbaum, and S. Rebelo, "Labor hoarding and the business cycle", manuscript, Northwestern University.

*Sample period 1 is 1955:3-1969-4. Sample period 2 is 1970:1-1984:1.

**Numbers in parentheses correspond to standard errors.

***Numbers in brackets refer to the probability value of the test statistic used by Burnside, Eichenbaum, and Rebelo (1990) to test whether a model and data moment are the same in population.

percent in the second period. This shows that the main substantive RBC claim—technology shocks account for most of the variability in aggregate output—is *very* sensitive to the presence of labor hoarding. I conclude that introducing labor hoarding into the analysis seriously undermines the main substantive claim of RBC theorists.

The Solow residual and government consumption

Before leaving my discussion of the Labor Hoarding Model, let me point to one more bit of subsidiary evidence in favor of that model relative to existing RBC models. Hall (1988, 1989) has emphasized the fact that the Solow residual appears to be correlated with a variety of objects like government consumption as measured by military expenditures.[22] Existing RBC models imply that this correlation coefficient ought to equal zero. To understand the quantitative implications of our model for this correlation we proceeded as in Hall (1988) and estimated the regression coefficient b_g, of the growth rate of the Solow residual on the growth rate of our measure of government consumption. Using the whole sample period the estimated value of b_g equals .187 with a standard error equal to .07. The probability limit of b_g implied by our model equals .104 with a standard error of .024. Burnside, Eichenbaum, and Rebelo tested the hypothesis that the two regression coefficients are the same in population and found that this null hypothesis cannot be rejected at conventional significance levels. There is, however, somewhat more evidence against the null hypothesis once we allow for a break in the sample period. The probability value of our test statistic was .9999 and .008 in the first and second subsamples, respectively.[23] So while there is virtually no evidence against the null hypothesis in the first subsample, there is substantial evidence against it in the second subsample. Nevertheless, it is clear that the Labor Hoarding Model does substantially better than standard RBC models on this dimension of the data.

Conclusion

In this article I have tried to assess the main substantive contention of RBC models, namely the view that aggregate technology shocks account for most of the fluctuations in postwar U.S. aggregate output. My main

TABLE 5

Indivisible Labor Model—variability of output: subsamples

	σ_{ϵ}**	ρ_a	σ_{ym}	λ
Whole sample*	.0089	.986	.017	.81
	(.0013)	(.026)	(.006)	(.56)
Sample period 1*	.0060	.862	.017	1.69
	(.0022)	(.071)	(.007)	(1.51)
Sample period 2*	.0101	.884	.028	1.42
	(.0015)	(.065)	(.005)	(.65)

SOURCE: C. Burnside, M. Eichenbaum, and S. Rebelo, "Labor hoarding and the business cycle," manuscript, Northwestern University.

*Whole sample corresponds to the sample period 1955:3-1984:4. Sample period 1 is 1955:3-1969:4. Sample period 2 is 1970:1-1984:1.

**Numbers in parentheses correspond to standard errors.

TABLE 6

Labor Hoarding Model—variability of output: subsamples

	σ_{ϵ}**	ρ_a	σ_{ym}	λ
Whole sample*	.0072	.977	.015	.58
	(.0012)	(.029)	(.001)	(.14)
Sample period 1*	.0042	.869	.011	.71
	(.0006)	(.043)	(.001)	(.20)
Sample period 2*	.0067	.882	.017	.52
	(.0006)	(.061)	(.001)	(.12)

SOURCE: C. Burnside, M. Eichenbaum, and S. Rebelo, "Labor hoarding and the business cycle," manuscript, Northwestern University.

*Whole sample corresponds to the sample period 1955:3-1984:4. Sample period 1 is 1955:3-1969:4. Sample period 2 is 1970:1-1984:1.

**Numbers in parentheses correspond to standard errors.

conclusion is that the evidence presented by RBC analysts is too fragile to justify this strong claim. It does not seriously undermine the traditional view that shocks to aggregate demand are the key source of impulses to the business cycle.

However, the RBC literature has succeeded in showing that dynamic stochastic general equilibrium models can be used to successfully organize our thoughts about the business cycle in a quantitative way. One cannot help but be impressed by the ability of simple RBC models to reproduce certain key moments of the data. In my view, too much progress has been made to revert to the nihilism of purely statistical analyses of the data. Certainly we need to know the facts. But designing good policy requires more than atheoretic summaries of the data. Good policy design requires empirically plausible structural economic models. The achievements of the RBC literature reinforce my optimism that progress is possible. The failures of that literature reinforce my view that we have some way to go before we can declare success.

FOOTNOTES

[1]See, for example, Summers (1986).

[2]This is not quite correct in a general equilibrium context. If consumers/labor suppliers own the goods producing firms, then there is also an income effect associated with a technology shock. If leisure is a normal good, then, other things equal, the labor supply curve would shift inwards in response to a positive technology shock. Christiano and Eichenbaum (1990) show that when a technology shock is not permanent the quantitative impact of this effect is negligible.

[3]See Aiyagari, Christiano, and Eichenbaum (1990) for a discussion of the effects of government purchases in the stochastic one sector growth model.

[4]See, for example, Kydland and Prescott (1982, 1989).

[5]See, for example, Hansen (1988).

[6]See Christiano and Eichenbaum (forthcoming).

[7]See, for example, Prescott (1986).

[8]See, for example, Kydland and Prescott (1982), Hansen (1985), Prescott (1986), Kydland and Prescott (1988), and Backus, Kehoe,and Kydland (1989).

[9]See King and Rebelo (1988). Also, in recent, work Kuttner (1990) has shown that the cyclical component of HP filtered data resembles one concept of potential real GNP quite closely.

[10]Our point estimates of α, θ, δ, ρ_a, σ_{ϵ}, ρ_g, and σ_{μ} equal .655 (.006), 3.70 (.040), .021 (.0003), .986 (.026), .0089 (.0013), .979 (.021), and .0145 (.0011). See Burnside, Eichenbaum, and Rebelo (1990) for details.

[11]The data and econometric methodology underlying these estimates are discussed in Burnside, Eichenbaum, and

Rebelo (1990). Our point estimates of α, θ, δ, ρ_a, and σ_ϵ, equal .655 (.006), 3.70 (.040), .021 (.0003), .986 (.026), and .0089 (.0013). Numbers in parentheses denote standard errors.

[12]See Hansen (1988) and Christiano and Eichenbaum (1990).

[13]Including government in the model does have important implications for the model's predictions along other dimensions of the data such as the correlation between average productivity and hours worked. See Christiano and Eichenbaum (forthcoming).

[14]Our point estimate of σ_{yd} is .019 with standard error of .002.

[15]See Burnside, Eichenbaum, and Rebelo (1990).

[16]The method used by Burnside, Eichenbaum, and Rebelo (1990) to estimate the model's structural parameters amounts to an exactly identified version of Hansen's (1982) Generalized Method of Moments procedure. Presumably the confidence interval could be narrowed by imposing more of the model's restrictions, say via a maximum likelihood estimation procedure or an over-identified Generalized Method of Moments procedure. Using such procedures would result in substantially different estimates of Ψ, making comparisons with the existing RBC literature very difficult. See Christiano and Eichenbaum (forthcoming) for a discussion of this point.

[17]Gordon (1979) presents evidence on this general phenomenon which he labels the "end-of-expansion-productivity-slowdown". McCallum (1989) also documents a similar pattern for the dynamic correlations between average productivity and output.

[18]It follows that labor must be compensated for working harder. We need not be precise about the exact compensation scheme because the optimal decentralized allocation can be found by solving the appropriate social planning problem for our model economy.

[19]For this model our point estimates of α, θ, δ, ρ_a, σ_ϵ, ρ_g, and σ_μ equal .655 (.006), 3.68 (.033), .021 (.0003), .977 (.029), .0072 (.0012), .979 (.021), and .0145 (.0011). See Burnside, Eichenbaum, and Rebelo (1990) for details.

[20]In ongoing research Craig Burnside and I are investigating this issue.

[21]See Perron (1988).

[22]Hall (1989) argues that time varying effort is not a plausible explanation of this correlation. To show this, he first calculates the growth rate of effective labor input required to explain *all* of the observed movements in total factor productivity. From this measure he subtracts the growth rate of actual hours work to generate a time series on the growth rate in work effort. He argues that the implied movements in work effort are implausibly large. This calculation does not apply to our analysis because it presumes that there are *no* shocks to productivity, an assumption which is clearly at variance with our model.

[23]In the first sample the point estimate of b_g is .0798 with standard error .0795. The value of b_g that emerges from our model is .0797 with a standard error of .0259. For the second sample the point estimate of b_g is .280 with a standard error of .099, while the value of b_g implied by the model is .0225 with a standard error of .004.

REFERENCES

Aiyagari, S. Rao, Lawrence J. Christiano, and Martin Eichenbaum, "The output, employment, and interest rate effects of government consumption," Working Paper Series, *Macro Economic Issues*, Research Department, Federal Reserve Bank of Chicago, WP-90-91, 1990 .

Backus, David K., Patrick J. Kehoe, and Finn E. Kydland, "International trade and business cycles," Federal Reserve Bank of Minneapolis, Working Paper 425, 1989.

Blanchard, Olivier J., "A traditional interpretation of macroeconomic fluctuations," *American Economic Review*, 79, 1989, pp. 1146-1164.

Burnside, Craig, Martin Eichenbaum, and Sergio T. Rebelo, "Labor hoarding and the business cycle," Manuscript, Northwestern University, 1990.

Christiano, Lawrence J., "Why is consumption less volatile than income?" Federal Reserve Bank of Minneapolis, *Quarterly Review*, 1, 1987, pp. 2-20.

Christiano, Lawrence J., and Martin Eichenbaum, "Unit roots in real GNP—Do we know and do we care?," *Carnegie-Rochester Conference Series on Public Policy: Unit Roots, Investment Measures and Other Essays*, Allan H. Meltzer, ed., 32, 1990, pp. 7-62.

Christiano, Lawrence J., and Martin Eichenbaum, "Current real business cycle theories and aggregate labor market fluctuations," *American Economic Review*, forthcoming.

Evans, Charles L., "Productivity shocks and real business cycles," Manuscript, University of South Carolina, 1990.

Fair, Ray, *The Short Run Demand for Workers and Hours*, North-Holland Publishing Company: Amsterdam, 1969.

Gordon, Robert J., "The end-of-expansion phenomenon in short-run productivity behavior," *Brookings Papers on Economic Activity*, 2, 1979, pp. 447-61.

Hall, Robert E., "The relation between price and marginal cost in U.S. industry," *Journal of Political Economy*, 96, 1988, pp. 921-47.

Hall, Robert E., "Invariance properties of the Solow residual," The NBER, Working Paper 3034, 1989.

Hansen, Gary D., "Indivisible labor and the business cycle," *Journal of Monetary Economics*, 16, 1985, pp. 309-28.

Hansen, Gary D., "Technical progress and aggregate fluctuations," Manuscript, University of California, Los Angeles, 1988.

Hansen, Lars P., "Large sample properties of generalized method of moments estimators," *Econometrica*, 50, 1982, pp. 1029-54.

Hodrick, Robert J., and Edward C. Prescott, "Post-war U.S. business cycles: an empirical investigation," Manuscript, Carnegie-Mellon University, 1980.

King, Robert G., and Sergio T. Rebelo, "Low frequency filtering and real business cycles," Manuscript, University of Rochester, 1988.

Kuttner, Kenneth., "A new approach to non-inflationary potential GNP," manuscript, Federal Reserve Bank of Chicago, 1990.

Kydland, Finn E., and Edward C. Prescott, "Time to build and aggregate fluctuations," *Econometrica*, 50, 1982, pp. 1345-70.

Kydland, Finn E., and Edward C. Prescott, "The work week of capital and its cyclical implications," *Journal of Monetary Economics*, 21, 1988, pp. 343-60.

Kydland, Finn E., and Edward C. Prescott, "Hours and employment variation in business cycle theory," Institute for Empirical Economics, Discussion Paper 17, 1989.

Lucas, Robert E. Jr., "Capacity, overtime, and empirical production functions," *American Economic Review*, Papers and Proceedings, 6, 1970, pp. 1345-1371.

Lucas, Robert E. Jr., "Expectations and the neutrality of money," *Journal of Economic Theory*, 4, 1972, pp. 103-124.

Lucas, Robert E. Jr., "The effects of monetary shocks when prices are set in advance," Manuscript, University of Chicago, November, 1989.

McCallum, Bennett T., "Real business cycle models," *Modern Business Cycle Theory*, Robert J. Barro, ed., Harvard University Press, 1989, pp. 16-50.

Perron, P., "The great crash, the oil price shock, and the unit root hypothesis," *Econometrica*, 55, 1988, pp. 277-302.

Prescott, Edward C., "Theory ahead of business cycle measurement," Federal Reserve Bank of Minneapolis, *Quarterly Review*, 10, 1986, pp. 9-22.

Rogerson, R., "Indivisible labor, lotteries and equilibrium," *Journal of Monetary Economics*, 21, 1988, pp. 3-17.

Summers, Lawrence J., "Some skeptical observations on real business cycle theory," Federal Reserve Bank of Minneapolis, *Quarterly Review*, 10, 1986, pp. 23-27.

Conference Highlights

REBUILDING BANKING

The 27th annual Conference on Bank Structure and Competition

Chicago, Illinois
May 1-3, 1991

The 1991 Conference on Bank Structure and Competition, sponsored by the Federal Reserve Bank of Chicago, will focus on the regulatory reforms and management strategies needed to restore the health of the banking industry. This year's conference will feature:

Alan Greenspan, chairman of the Federal Reserve Board, presenting the keynote address;

A. W. Clausen, chairman of the executive committee of BankAmerica Corporation, discussing strategies for regaining competitiveness;

John P. LaWare, member of the Federal Reserve Board, **George M. Salem,** vice president of Prudential-Bache Capital Funding, and **Barry F. Sullivan**, chairman of First Chicago Corporation, presenting their views on the future of the banking industry during a panel discussion moderated by Chicago Fed President **Silas Keehn;**

John C. Dugan, deputy assistant secretary at the U.S. Treasury Department, **Kenneth A. Guenther,** executive vice president of the Independent Bankers Association, **Edward J. Kane,** Reese professor of banking at Ohio State University, and **Thomas C. Theobald,** chairman of Continental Bank, analyzing current legislative proposals for deposit insurance reform; and

Philip F. Bartholomew, principal analyst at the Congressional Budget Office, **John F. Bovenzi,** deputy to the chairman at the Federal Deposit Insurance Corporation, and **Robert E. Litan,** senior fellow at The Brookings Institution, examining the condition of the banking system.

In addition, the conference will include thought-provoking presentations on the future profitability of the banking industry, the early closure of capital deficient banks, deposit insurance pricing, and market value accounting.

The conference will be held at The Westin Hotel, 909 N. Michigan Ave., Chicago, on May 1, 2, and 3, 1991. For additional information, please write or call:

Betty Hortsman
Public Affairs Department
Federal Reserve Bank of Chicago
P.O. Box 834
Chicago, Illinois 60690-0834
Telephone (312) 322-5114

ECONOMIC PERSPECTIVES

Public Information Center
Federal Reserve Bank of Chicago
P.O. Box 834
Chicago, Illinois 60690-0834

BULK RATE
U.S. POSTAGE
PAID
CHICAGO, ILLINOIS
PERMIT N0. 1942

Do Not Forward
Address Correction Requested
Return Postage Guaranteed

FEDERAL RESERVE BANK
OF CHICAGO