WAGE MOVEMENTS AND THE LABOR MARKET

EQUILIBRIUM HYPOTHESIS

by

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Wage Movements and the Labor Market Equilibrium Hypothesis

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The view that aggregate monetary and fiscal policies cannot affect
unemployment in the long run is now accepted by both academic economists
and public officials.1/ Some academics were convinced early on that demand
management policies must have a neutral effect on real activity on the grounds
that money illusion could not persist indefinitely. Other academics and many
public officials were finally convinced when the predictions that continued
reflationary policies must ultimately produce a permanently higher inflation
rate without any reduction in unemployment were verified by the experience of
the 1970's.

This remarkable post-Keynesian revolution has led to a flurry of new
research activity aimed at building macroeconomic models that are consistent
with "the facts." Many of these models assume that markets, including labor

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1/ Eloquent statements of this view range from Milton Friedman [19] to the former
British Prime Minister James Callaghan [6].
markets, clear rapidly, standing the Phillips Curve relating price or wage changes to unemployment on its head. They posit that unemployment is determined by the discrepancy between expected future wages and prices and current wages and prices and reflects variations in the supply of labor. This influential interpretation of unemployment as the intertemporal substitution of leisure was first offered by Lucas and Rapping [27] and Lucas [28]. Its importance is twofold. First, it offers a convenient and tractable analytical mechanism for constructing models that incorporate unemployment and inflation and that are consistent with the proposition that aggregate government policy ultimately does not affect the level of resource utilization. Second, a serious labor market hypothesis must explain the key fact that employment moves cyclically and in a strong negative relationship with movements in the percentage of persons who say they would like to work but do not have jobs. The interpretation of employment fluctuations as the result of demand shifts up a short run labor supply curve that is very elastic because of intertemporal substitution offers a potential explanation for this key fact while simultaneously maintaining that labor supply and demand are continuously equal. Unemployment is then interpreted as a measure of the labor supply that would be forthcoming at the expected future wage relative to the labor supply that is forthcoming at the actual wage. The implication is that if the long run supply curve of labor is taken to be inelastic, then movements in unemployment and labor supply are interchangeable (after suitable normalization).

2/ See Barro [4], Sargent [32], and Fischer [18] for examples of such models.
This convenient analytical interpretation of unemployment is at complete odds with the conventional Keynesian view. In the latter, unemployment represents quantity constraints on labor supply that offer the possibility for mutually beneficial trades for workers and employers. It is this promise of increased resource utilization and its implied increase in the welfare of workers whose offers of labor supply have been frustrated that provides the basis for Keynesian policy activism. The widely held view that aggregate monetary and fiscal policies cannot affect unemployment in the long run has caused those interested in activist policies to look for new schemes, such as wage subsidies, public employment programs, and tariff and nontariff barriers, to increase employment. If the labor market equilibrium hypothesis is correct, however, then there are no unexploited and mutually beneficial trades to be made and these policies are neither desirable nor likely to be effective.

A crucial issue for empirical analysis is thus the compatibility of the equilibrium hypothesis with observed variations in employment, unemployment, and wages. Despite the continuing empirical work on the efficacy of monetary and fiscal policies, surprisingly little effort has been devoted to tests of whether intertemporal substitution can serve as a satisfactory structural explanation for movements in employment and unemployment. In this paper we report the results of some preliminary efforts to test the empirical consistency of the time series of wages and unemployment with what we shall term the labor market equilibrium.

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3/ Examples are Barro [14], McCallum [29], and Sargent [34].
hypothesis. We begin with a simple presentation that underlines the importance of the dynamic behavior of the time series of the real wage in assessing this theory. Since the intertemporal substitution theory assigns a key role in the explanation of movements in unemployment to movements in the differential between current and expected future real wage rates, we first ask whether this differential fluctuates at all. Remarkably enough, the answer to this question hinges in part on whether the aggregate real wage process obeys a random walk and in part on whether the variance in the innovation in aggregate real wages is large relative to the transitory cross-sectional variation in real wages. The former issue can best be addressed by aggregate time series data while the latter can only be addressed with longitudinal data. As a result, we first turn to a survey of the measured extent of microeconomic wage variability in longitudinal data and then to a discussion of econometric methods for putting the random walk proposition to a test. The data used for this latter purpose are a long U.S. annual time series and postwar quarterly time series for both the U.S. and the U.K. Next, using the same data we inquire into whether the observed fluctuations in the differential between current and expected future real wages are large enough compared to plausible external estimates of labor supply elasticities to account for a significant fraction of the observed time series variation in unemployment. Finally, we explicitly test the ability of a time series of measured differentials between the permanent and current real wage rate to explain the time series movements in unemployment.
I. The Wage Process and the Intertemporal Substitution Hypothesis

In its simplest form the intertemporal explanation for movements in unemployment starts from the labor supply function for the \( i^{th} \) worker

\[
(1) \quad h_{it} = \beta_0 + \beta_1 (w_{it} - w^*_it) + \beta_2 w^*_it + \nu_{it},
\]

where \( h_{it} \) is the logarithm of hours worked, \( w_{it} \) is the logarithm of the current wage rate, and \( w^*_it \) is an index of the expected future wage rate. Here \( \beta_1 > 0 \) is the short run supply elasticity and \( \beta_2 \) is the long run supply elasticity.

The theory assumes that the labor market clears, so that (1), together with (unspecified) labor demand functions, determines \( h_{it} \) and \( w_{it} \). Normal labor supply \( h^*_it \) may be defined as the value of (1) when \( v_{it} = w^*_it = 0 \), so that

\[
(2) \quad h^*_it - h_{it} = \beta_1 (w^*_it - w_{it}).
\]

Lucas and Rapping [27] observe that \( h^*_it - h_{it} \) is the proportion by which current employment falls short of normal labor supply and propose that this be taken as the behavioral interpretation of measured unemployment. Assuming a linear stochastic relationship between \( h^*_it - h_{it} \) and unemployment \( u_{it} \) leads to

\[
(3) \quad u_{it} = a_0 + a_1 (h^*_it - h_{it}) + \nu_{it} = a_0 + a_1 \beta_1 (w^*_it - w_{it}) + \nu_{it}.
\]
According to this interpretation unemployment is high when the expected future wage is high relative to the current wage. Variations in unemployment are thus a result of variations in the current wage relative to the expected future wage.  

At a minimum, then, in order to explain aggregate behavior the theory requires that the average value of \((w_{it}^* - w_{it})\) show cyclical fluctuations. It also requires that these fluctuations be large enough (given assumptions about \(\alpha, \beta, \gamma\)) to explain observed fluctuations in aggregate unemployment, \(u_t\), and that the movements in the average value of \((w_{it}^* - w_{it})\) and \(u_t\) be related.

A. The Expected Future Wage

To test these propositions about the aggregate behavior of unemployment it is necessary to generate a time series on \(w_{it}^*\) to be inserted into (3) and then to aggregate over individual workers. In order to do this we will suppose that the \(i^{th}\) worker’s real wage \(w_{it}\) may be described by the simple components-of-variance scheme:

\[
(w_{it}^* = w_i + \nu_i + \epsilon_{it})
\]

\(h/\) We can justify omission from (3) of the ratio of an index of expected future prices to current prices and the nominal interest rate if we assume that (a) interest rates reflect inflation expectations and (b) the real interest rate is constant. The latter assumption is not very appealing, and our work should be extended to account for it. Hall [22] analyzes this issue, but apparently assumes that \(w_{it}^*\) is constant instead. We return to a discussion of the role of nominal price effects on unemployment below.

\(s/\) This is a frequently used setup in studies with longitudinal data. See Heckman [23] for a useful survey of these models. Examples of its microeconomic implementation include Ashenfelter [3] and Lillard and Willis [26]. It is, of course, the basis for the macroeconomic setup in Lucas [28], although there the application is to nominal prices.
Here $w_i$ is a permanent component of the worker's real wage rate based on the worker's human capital and other characteristics, and without loss of generality we may assume that these terms sum to zero so that $\sum_{1}^{\infty} w_i = 0$. $w_t$ represents the aggregate real wage rate and $\epsilon_{it}$ is the transitory part of an individual's wage rate. For convenience we take the $\epsilon_{it}$ to be independent normally distributed random variables with mean zero and variance $\tau^2$ that are uncorrelated with $w_i$ and $w_t$.

In order to calculate an expected future real wage rate the worker must first calculate a series of forecasts of future real wage rates $\hat{w}_{it+1}$, ..., $\hat{w}_{it+m}$ over some arbitrary future period of length $m$. Given these forecasts we will simply define $w^*_{it}$ as

$$w^*_{it} = \sum_{k=1}^{m} Y_{it+k},$$

where $\sum_{k=1}^{m} Y_{it+k} = 1$.

Assuming that each worker has knowledge of $w_i$ and the distribution of $\epsilon_{it}$, the forecasts $\hat{w}_{it+k}$ will be the sum of $w_i$ and each worker's forecast of the aggregate wage $w_{t+k}$. The question naturally arises as to how these forecasts of the aggregate wage might be generated. Empirical work by Neftci [31] and Sargent [35] suggests a simple autoregressive forecasting device might be suitable. In particular, Neftci and Sargent find no evidence that prediction of $w_t$ can be improved by using lagged values of actual aggregate employment $h_t$. In this case forecasts may be based on the $n$-th order autoregression

$$y_t = \lambda y_{t-1} + b' + \epsilon_t',$$
where we have used the matrix notation $y_t = [w_t, \ldots, w_{t-n+1}]'$, $\lambda$ is a matrix of order $(n \times n)$ with the coefficients $\lambda_j$ as its first row and units below the diagonal, and $b'$ and $\varepsilon_t'$ are $n$-component column vectors with a constant $b$ and a serially uncorrelated disturbance $\varepsilon_t$ with variance $\sigma^2$ in their first rows and zeros in their remaining rows.

In what follows we will maintain (3), (4) and (5) and assume that all workers have knowledge of the parameters of (6). The only question remaining, then, is what additional information workers are assumed to have at the time the forecasts $\hat{\gamma}_{t+k}$ are generated. It is useful to distinguish two cases. In the first case workers have knowledge of the current aggregate wage rate $w_t$, while in the second case they do not.

B. Complete Information

Assuming that information on $y_t = [w_t, w_{t-1}, \ldots, w_{t-n+1}]'$ is available, the $k$-step-ahead forecasts of the aggregate wage using (6) are of the form

$$\hat{\gamma}_{t+k} | y_t = \lambda' y_t + \sum_{i=0}^{k-1} \lambda_i b', \quad (7)$$

where the notation $\hat{\gamma}_{t+k} | y_t$ indicates the forecast of $\gamma_{t+k}$ based on the current and lagged values of the aggregate wage, $y_t$. Using (4), (5), and (7) the value of the expected future wage for the $i^{th}$ individual is then

$$w_{1t}^* | y_t = \Sigma y_k (v_i + \hat{\gamma}_{t+k} | y_t) \quad (8)$$

$$= v_i + \Sigma y_k (\hat{\gamma}_{t+k} | y_t)$$

$$= v_i + w_t^* y_t,$$
where \( \hat{w}_t | y_t \) is a forecast of the aggregate wage that is common to all workers.

Inserting (8) into (3) and aggregating (taking expectations) over workers then gives the aggregate unemployment function

\[
(3a) \quad \hat{u}_t = \alpha_0 + \alpha_1 [\hat{w}_t | y_t] - w_t + v_t.
\]

With this setup the question of whether \( (\hat{w}_t | y_t) - w_t \) fluctuates at all translates into the statistically tractable question of whether \( w_t \) obeys a random walk. For in the random walk case \( (\lambda_1 = 1, \lambda_2 \ldots \lambda_n = 0) \), the forecasts (7) are

\[
(7a) \quad \hat{y}_{t+k} | y_t = w_t + bk
\]

and the expected future aggregate wage is simply

\[
(9) \quad \hat{w}_t | y_t = w_t + b \sum_{k=1}^{m} \gamma_k k.
\]

The difference \( (\hat{w}_t | y_t) - w_t \) is thus always a constant, which implies from (3a) that, apart from measurement error, aggregate unemployment should be constant also. Roughly the same conclusion applies to movements in employment about trend. Acceptance of the random walk forecast device for aggregate real wage rates thus leaves no variation in the discrepancy between expected future wage rates and actual wage rates, so that movements in employment and unemployment can hardly be attributed to this discrepancy.

C. Incomplete Information

The preceding analysis is consistent with the argument in Lucas and Rapping [27], but it is not entirely faithful to the view in Lucas [28] and
elsewhere that fluctuations in unemployment are also caused by rational errors in beliefs about the value of the current aggregate wage and/or in the resulting errors in the forecast of future wages based on these beliefs. Individual workers (or groups of workers) may have only imperfect information about the aggregate wage at time $t$. These workers must then depend on expectations based on the current real wage in the markets in which they participate and on the values of the aggregate wage in the past to make current decisions.

To implement this notion we suppose that in period $t$ workers observe (a) their own real wage rate $w_{it}$ and (b) the lagged values of the aggregate real wage $y_{t-1}$, but they do not observe $w_t$. The problem for each worker is to infer $w_t$ from the available information so that this inference may be used with $w_i$ and (6) to forecast future wage rates. Under the assumptions we have made, however, $w_t$ and $w_{it} - w_i$ are jointly normally distributed so that the conditional mean (and forecast by the $i$th individual) of $w_t$ given $w_{it} - w_i$ and $y_{t-1}$ is:

$$
(10) \quad \hat{w}_t | w_{it}, w_i, y_{t-1} = (1-\Theta)(w_{it} - w_i) + \Theta \gamma'(y_{t-1} + b')
$$

$$
= (1-\Theta)(w_{it} - w_i) + \Theta \gamma'(\hat{y}_t | y_{t-1})
$$

where $\gamma'$ is an $n$-component row vector with a unity in the first column and zeros elsewhere, $\hat{y}_t | y_{t-1}$ indicates the forecast of $y_t$ using $y_{t-1}$, from

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5/ Given the assumptions in the text $w_t$ and $w_{it} - w_i$ are bivariate normal with a fully specified mean vector and covariance matrix. The conditional distribution of $w_t$ given $w_{it} - w_i$ and $y_{t-1}$ is then normal with the mean of $w_t$ given by (10) and its variance equal to $6\sigma^2$. See, for example, Dhrymes [14, p. 16].
(6), and \( \theta = \tau^2/(\tau^2 + \sigma^2) \). Equation (10) is a scheme for the inference of \( w_t \) by an individual worker that makes its prediction a weighted average of the observed deviation \( w_{it} - w_i \) and \( y_t^* | y_{t-1} \), the forecast of the aggregate wage \( w_t \) based only on its past values. In this framework \( \theta \) is small when most of the variation in individual wages comes from aggregate time series shocks, in which case an individual's wage rate \( w_{it} \) may be a useful indicator of \( w_t \). Alternatively, \( \theta \) is large when most of the variation in individual wage rates is cross-sectional, and in this case past values of the aggregate wage rate will be a better indicator of \( w_t \).

Forecasts of future wage rates by the \( i^{th} \) worker will now be made by inserting (10) into (6) and adding \( w_i \) to get

\[
(11) \quad y_{it+k}^* | w_{it}, w_i, y_{t-1} = \delta w_i + \lambda^k \left[ (1-\theta)y_{it}^* + \theta(y_t^* | y_{t-1}) \right] + \sum_{i=0}^{k-1} \lambda^i b_i
\]

where \( \delta \) is a column vector of \( n \) units and where the vector \( y_{it}^* = [w_{it} - w_i, w_{t-1}, \ldots, w_{t-n+1}]' \). Summing over the elements of (11) using the definition of the future wage index (5) then gives

\[
(12) \quad w_{it}^* | w_{it}, w_i, y_{t-1} = w_i + (1-\theta)(w_*^* | y_{it}) + \theta(w_*^* | y_{t-1}).
\]

According to (12), the \( i^{th} \) worker's expected future wage contains a permanent component \( w_i \) and a cyclical component that is a weighted average of (a) the forecasted future aggregate wage based on the \( i^{th} \) worker's own wage deviation \( w_{it} - w_i \) and the previous values of the aggregate wage, and (b) the forecasted future aggregate wage based solely on the previous values of the aggregate wage.

The first part of this forecast varies across individuals, while the second part is common to all individuals. The rational worker's current wage \( w_{it} \) receives less weight in this forecast the greater is the (random) cross-sectional variation in wage rates (\( \tau^2 \)) relative to the (random) time series variation in wage rates (\( \sigma^2 \)).
The unemployment function (3) for the $i$th worker is

$$u_{it} = \alpha_0 + \alpha_1 \beta_1[\{w_{it}^* \mid w_{it}, v_i, y_{i,t-1}\} - v_{it}] + v_{it}$$

$$= (\alpha_0 + \alpha_1 \beta_1 w_i) + \alpha_1 \beta_1[\{w_{it}^* \mid y_{it}\} - w_{it}] - \alpha_1 \beta_1 \theta[\{w_{it}^* \mid y_{it}\}$$

$$- (w_{t}^* \mid y_{t-1})] + v_{it},$$

where the second line follows from the substitution of (12). Since the aggregate unemployment function is obtained by averaging over $i$ and since $E(w_{t}^* \mid y_{it}) = v_{t}^* \mid y_{t}$ and $E(w_{it}) = v_{t}$, it is of the form

$$u_{t} = \alpha_0 + \alpha_1 \beta_1[\{w_{t}^* \mid y_{t}\} - v_{t}] - \alpha_1 \beta_1 \theta[\{w_{t}^* \mid y_{t}\} - (w_{t}^* \mid y_{t-1})] + v_{t}.$$ 

Equation (3c) contains the aggregate deviation of the expected future real wage from the current real wage based on complete information as did (3a), but it also contains the revision of the forecast of the future real wage made because of the new information provided by observation of $w_{t}$. This forecast revision is a linear function of $\epsilon_{t}$, the aggregate innovation or "surprise" in the current real wage. The importance of this forecast revision to movements in unemployment depends critically on the value of $\theta$, the fraction of real wage variation that represents relative transitory wage differences among individuals. If this fraction is large so that aggregate wage changes are poorly perceived at the time labor supply decisions are made, then these surprises may have an important effect on unemployment. When they occur workers will erroneously (but rationally) believe that their actual unexpected wage increases are "good draws" that will not be repeated and that they should capitalize on them now by increasing their current labor supply.
As we have seen, when the forecast device (6) is a random walk, the term \((v_t^*|y_t) - w_t\) does not vary. When there is imperfect information about the current value of \(w_t\), however, the term \((v_t^*|y_t) - (v_{t-1}^*|y_{t-1})\) will vary even if (6) is a random walk. For in this case the random walk forecasting device implies forecasts

\[
(7b) \quad \hat{w}_{t+k}^*|y_{t-1} = w_{t-1} + b(k+1)
\]

and an expected future aggregate wage of the form

\[
(13) \quad w_t^*|y_{t-1} = w_{t-1} + b + b\gamma_k k
\]

\[= w_t + b\gamma_k k - \epsilon_t
\]

\[= v_t|y_t - \epsilon_t
\]

where the last line follows from (9). The forecast revision \((v_t^*|y_t) - (v_{t-1}^*|y_{t-1})\) is equal to the current period forecast error in the random walk case. Thus, in this special case unexpected increases in the real wage rate, \(\epsilon_t\), tend to decrease unemployment by an amount equal to the product of \(\gamma\) and the labor supply elasticity.

D. Components of Wage Variation

The preceding discussion emphasizes the importance of knowledge about the extent of wage variation due to aggregate wage innovations, \(\sigma^2\), relative to the extent of wage variation due to cross-section differences \(\tau^2\). In principle \(\tau^2\) may be measured from longitudinal data on individual workers.
using the components-of-variance scheme (4), and some estimates are available. Cline [9] uses nine years of data on white males from the Michigan Income Dynamics Survey and estimates $r^2 = .09$ after the individual effects $w_i$ are taken out. He also provides an estimate of $r^2 = .08$ when individual effects $w_i$ are removed and the estimation of $r^2$ is confined to workers who do not change employers. This last estimate may, of course, be downward biased since job changes may be the result of unexpected wage offers. Unfortunately, Cline does not control for the time effects $w_t$ in his estimation scheme, and this may also bias his estimates. 

To see if we could improve on these estimates we also fitted equation (4) to a sample of 1496 male workers from the National Longitudinal Survey (Parnes) data. A simple way to do this is merely to difference out the individual effects $w_i$ and fit

$$(4a) \quad \Delta w_{it} = \Delta w_t + (\epsilon_{it} - \epsilon_{it-k})$$

SIM/ Similar estimates from the same data have been made by Gordon [21]. The results obtained by Lillard and Willis [26] are, unfortunately, for earnings rather than wage rates.

SIM/ From the sample of males aged 45-59 in 1966 we selected all those (1) who were at work or with a job in each of the sample weeks in 1967, 1969, and 1971, (2) who were employed as wage and salary workers in either the private or public sectors, and (3) for whom an hourly wage rate is available. For hourly rated workers the reported wage is used, but for non-hourly rated workers the wage is the ratio of earnings per pay period to hours worked per pay period. Although the former make up less than ten per cent of the sample we also performed the analysis for hourly rated workers separately on the grounds that measurement error might bias upward the estimates of $r^2$ for other workers. Though based on a very small sample, the estimates of $r^2$ for hourly rated workers were even larger than those reported in the text.
to cross-section data \( k \) years apart.\(^2\)

The estimated residual variance from this equation is then an estimate of \( 2\tau^2 \). Using the two years 1967 and 1969 we obtained \( \Delta W_t = .133 \) (with estimated standard error \(.010\)) and \( \tilde{\tau}^2 = .082 \) (with estimated standard error \( 10^{-4}(.09) \).\(^10\) Using the two years 1969 and 1971 we obtained \( \Delta W_t = .104 \) (with estimated standard error \(.013\)) and \( \tilde{\tau}^2 = .123 \) (with estimated standard error \( 10^{-3}(.02) \)). These estimates of \( \tau^2 \) are therefore of the same order of magnitude as those that have already appeared in the literature. Below we report estimates of \( \sigma \) from several alternative time series models. At an annual level all of these estimates of \( \sigma \) are around .017, implying an estimate of \( \sigma^2 \) of around .0003. Taken with the available estimates of \( \tau^2 \), these results imply that \( \Theta \) is essentially unity.\(^11\) In other words, the transitory

\(^2\)This implicitly assumes that the same price index is applicable to each worker and is thus indistinguishable in these data from the change in the aggregate wage \( \Delta W_t \). Estimates of \( \Delta W_t \) are then estimates of \( \Delta W_t + \Delta p_t \), where \( \Delta p_t \) is the change in the common price index. The variability in the prices individuals face is an interesting topic for research that might be pursued along the lines in Michael [30], and we hope to do so at some future date.

\(^10\)Lillard and Willis [26] find some (1st order) serial correlation in \( \epsilon_{it} \) in their results for earnings. It may be shown that the analysis in the previous section of optimal forecasts under imperfect information will remain intact if \( \tau^2 \) is interpreted as the variance of the innovation in \( \epsilon_{it} \). It is easy to demonstrate under this reinterpretation of \( \tau^2 \) and the assumption that \( \epsilon_{it} \) obeys a first order autoregressive process that the residual variance from (4a) is an estimate of \( 2(1-\rho^2)/(1-\rho^2)^{-1} \tau^2 = 2\tau^2 \). Consequently, our analysis is not sensitive to \( \rho \).

\(^11\)Using the random walk setup, for which we find considerable support in the sequel, it is actually possible to estimate \( \sigma^2 \) from the two estimates of \( \Delta W_t \) reported in the text. Using (6) we may write \( \Delta W_t = W_t - W_{t-2} = 2\epsilon_t + \epsilon_{t-1} + \epsilon_t \) so that \( \sum (\Delta W_t - \bar{\Delta W})^2 \) is an estimate of \( \sigma^2 \). Since price changes were roughly comparable over the 1967-69 and 1969-71 periods the estimate of \( \sigma^2 \) from these data is \((.015)^2\), nearly identical to the estimate in the text. Of course, this procedure can hardly be taken seriously since it is based on only two observations, but it is indicative of how a more detailed analysis might be carried out.
cross-sectional variation in wage rates is enormously greater than the
transitory time-series variation in aggregate wage rates. This implies
that models of the labor market based on incomplete information may be
more empirically relevant than those based on complete information.

Of course, all the estimates of $\tau^2$ obtained to date may be a result
of considerable measurement error in the microeconomic measurement of wage
rates. Such measurement error tends to bias estimates of $\tau^2$ upwards, and
the available estimates are no doubt very sensitive to this problem. Until
better data are available, however, the possibility that there is very sub-
stantial transitory cross-sectional wage variability simply cannot be ruled
out.

E. Nominal Price Movements and Labor Supply

The preceding analysis has emphasized the connection between the
deviation of actual from expected future real wage rates and unemployment.
Nominal wage and price movements do not appear separately, even though the
connection between nominal movements in wages or prices and unemployment is
one of the major issues considered by Lucas and Rapping [27], Lucas [28],
and Sargent [35]. It seems especially appropriate to comment on this issue
here since our failure to consider it is both an important limitation of the
results reported below and a major area for further research.

There are three ways that the nominal price level and one way that
the nominal wage rate might enter the aggregate unemployment functions spec-
ified above. First, nominal prices and/or wages might enter an aggregate
unemployment function such as (3c) where imperfect information is explicitly
acknowledged if the forecasting devices used by individual consumer-workers are different for these two variables. In this case "surprises" in nominal wages and prices would enter the aggregate unemployment function with coefficients that differ by the extent to which the transitory cross-section variation relative to the transitory time series variation in nominal wage rates and in price indexes differ. The development and implementation of such a model might be a useful topic for further research.

Second, the ratio of expected future prices to current prices may have a significant role to play in the micro-level unemployment function (3) through variations in the real interest rate. In this model variations in real interest rates may affect unemployment (or labor supply) because of substitution between the future consumption of leisure and the current consumption of leisure and because of substitution between the future consumption of goods and the current consumption of leisure. In this paper we have concentrated on the extent to which the substitution of current for future leisure in response to real wage movements may serve as an explanation for movements in unemployment because this seems empirically more plausible. Nevertheless, much of the empirical work in Sargent [32] and Lucas [28] focuses implicitly on the substitution between goods and leisure and further research might usefully involve the construction of a more complete model.12/

12/ However, Altonji's (1979) estimates of a rational expectations version of the Lucas and Rapping model incorporate the effects of price and interest rate movements and imperfect information about prices and real wages and are not much more successful than the estimates we report below.
II. Testing the Random Walk Hypothesis

As we have seen, whether the deviation \( \omega_t \) fluctuates at all depends on whether the real wage process follows a random walk. Our interest in this case was inspired in part by the empirical results in Table 1, which correspond to fitting equation (6) to U.S. annual data where the dependent variable is the first-difference in the logarithm of the real wage. Column (1) corresponds to the fit of a random walk with drift, while the remaining columns report the results of relaxing this assumption and adding lagged values of the level of the logarithm of the real wage to the regression. To our astonishment, a Box-Pierce test of the first 12 sample autocorrelation coefficients indicates that the hypothesis that the residuals for the random walk model are white noise cannot be rejected at any reasonable significance level. Furthermore, the conventional F-ratios for testing the hypothesis \( \lambda_j = 1 \) and \( \lambda_j = 0 \) \((j > 1)\) also indicate that the random walk hypothesis cannot be rejected in these data. Finally, F-tests with first, second, and third order autoregressions in the first-differences in the logarithm of the real wage (not reported) also provide no evidence against the random walk model. However, there are objections to each of these tests that require discussion.

A. Test Procedures

First, the power of the Box-Pierce test for the relevant sample sizes may be very small if the true model is not grossly different from a random walk.\(^{13}\) The F-tests of the random walk hypothesis against the specific

\(^{13}\)See the Monte Carlo results in Dickey and Fuller [16], but note that the model they study does not contain an intercept.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
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**Table 1**

**Coefficients:** (t-values in parentheses)

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**Dependent Variable: y**

**H0:** The average correlation for I have a, 1969-76.

**H1:** The average correlation without the trend of the I have a, 1969-76.
alternatives offered in Table 1 might be expected to have more power. However, a second objection concerns the use of the F-ratio to test for a random walk, which is a nonstationary process. The asymptotic justification for assuming that the conventional F-ratio from an autoregressive model has an F distribution under the null hypothesis requires that the model be stationary when the null hypothesis is true. The F-tests based on first differences circumvent this problem, but they raise a third objection. They are a test of the random walk hypothesis only if one maintains that (6) has a unit root, which is a big step toward assuming that the null hypothesis is true. To see this note that the unit root may be isolated as a coefficient by writing (6) as

\[ w_t = \delta + \phi_1 w_{t-1} + \sum_{j=2}^{n} \phi_j (w_{t-j+1} - w_{t-j}) + \epsilon_t \]

where \( \phi_1 = \sum_{i=1}^{n} \lambda_i \) and \( \phi_j = -\sum_{i=1}^{j-1} \lambda_i \) for \( j = 2 \ldots n \).

If there is a unit root, \( \phi_1 = 1 \). From the identities relating the \( \phi \)'s and \( \lambda \)'s it is clear that (6a) is a random walk with drift only if \( \phi_1 = 1 \) and \( \phi_j = 0 \) (for \( j > 1 \)). Estimation in first differences is therefore justified only if one maintains \( \phi_1 = 1 \). Testing whether \( \phi_2 = \ldots = \phi_n = 0 \) amounts to testing a necessary, but not a sufficient condition for a random walk. If \( \phi_1 < 1 \), differencing will introduce an infinite order moving average component into the error term. Of course, the Box-Pierce test of the residuals from the random walk model should detect this component in a large enough sample even if \( \phi_2 = \ldots = \phi_n = 0 \). Likewise, the estimators of \( \phi_2 \ldots \phi_n \) are inconsistent.

1h/ See Fuller [20, pp. 373-374].
in this case and the $F$-test might incorrectly reject the hypothesis $\phi_2 = \ldots = \phi_n = 0$ but correctly reject the random walk hypothesis if $\phi \neq 1$, although the bias could also run in favor of the random walk hypothesis. In either case, the power of these tests may be small.

In sum, what is needed is a more powerful test than the Box-Pierce procedure for the joint hypotheses $\lambda_1 = 1$ and $\lambda_2 = \ldots = \lambda_n = 0$. Unfortunately, the joint (asymptotic) distribution of the least squares estimators of these parameters is not known in this case.\textsuperscript{15} However, using (6a) it is possible to perform a Bonferroni test of the random walk hypothesis based on separate tests of the sub-hypotheses that $\phi_1 = 1$ and $\phi_2 \ldots \phi_n = 0$ if one maintains that at most one root is equal to 1 and no roots are greater than 1 (in absolute value). Fuller [20] presents the empirical distribution of the conventional "$t$" statistic for $\phi_1$ under the null hypothesis that $\phi_1 = 1$.\textsuperscript{16}

This permits a test of the hypothesis $\phi_1 = 1$. He also shows that the distribution of the least squares estimator of $\phi_2 \ldots \phi_n$ around the true values converges to the distribution of the least squares estimator when $\phi_1 = 1$ is.

\textsuperscript{15} Fuller [20], Dickey and Fuller [16], and Stigum [36] provide brief summaries of what is known about the distribution of the least squares estimator under alternative assumptions about the $\lambda$'s as well as the appropriate references.

\textsuperscript{16} See Fuller [20, p. 373]. The table is based on the work of Dickey [15]. Actually, the Monte Carlo study concerns a first order autoregressive model with $\phi_1 = 1$. However, Fuller shows that the limiting distribution of $\phi_1$ in the $n$th order autoregressive case with one unit root is the same as the distribution of $\lambda_1$ in the first order autoregressive case with $\lambda_1 = 1$. Dickey and Fuller [16] report that if one assumes $\delta \neq 0$ (which we maintain) then the limiting distribution of the "$t$" statistic for $\phi_1$ is normal. Whether the normal distribution or conventional "$t$" distribution is a better approximation to the distribution of the "$t$" statistic for $\phi_1 = 1$ is an open question. The results reported in this paper are not sensitive to this, however. Note that the limiting distribution of the "$t$" statistic for $\phi_1$ when a time trend is added to the autoregressive model is independent of the value of $\delta$.\textsuperscript{16}
imposed. Since the distribution of the latter estimator is asymptotically normal, and the least squares estimator of \( \phi_2 \ldots \phi_n \) is also asymptotically normal if \( |\phi_1| < 1 \), the least squares estimator of \( \phi_1 \), \ldots, \( \phi_n \) is asymptotically normal whether \( |\phi_1| = 1 \) or \( |\phi_1| < 1 \). Consequently, we use the standard F-ratio with the F distribution to test the hypothesis that \( \phi_2 = \ldots \phi_n = 0 \). We compute the marginal significance levels of the individual tests and claim to reject the random walk hypothesis at a significance level less than or equal to .10 if the hypothesis \( \phi_1 = 1 \), or the hypothesis \( \phi_2, \ldots, \phi_n = 0 \) (or both) are rejected at the .05 significance levels. The size of the test is understated to the extent that the probability that both sub-hypotheses will be rejected is greater than zero.

There is an additional difficulty with the F-tests reported in Table 1 that concerns the specific formulation of the alternative hypothesis. If all roots of the autoregressive model of the wage are less than 1 in absolute value, the implication is that the mean of \( \omega_t \) conditional on its lagged values converges to a constant. Consider the following specification of the real wage as the sum of a linear time trend and an autoregressive error component:

\[
(14) \quad \omega_t = c + d \cdot T + \eta_t \; ; \; \eta_t = \sum_{i=1}^{n} \lambda_i \eta_{t-i} + \epsilon_t
\]

After repeated substitutions one obtains the autoregressive representation

\[
(14a) \quad \omega_t = \left[1 - \sum_{i=1}^{n} \lambda_i \right] \left[c + d \cdot T\right] + d \sum_{i=1}^{n} \lambda_i \omega_{t-i} + \sum_{i=1}^{n} \lambda_i \omega_{t-i} + \epsilon_t
\]

which reduces to (6) (with \( \delta = d \sum_{i=1}^{n} \lambda_i \)) when \( \sum_{i=1}^{n} \lambda_i = 1 \). Of course this is the condition that \( \eta_t \) and the autoregressive representation of \( \omega_t \) have unit
roots. The upshot of this discussion is that if one maintains (14) instead of (6), then a trend term (with a coefficient of zero under the null hypothesis) should be included in the autoregressions. Below we report results for both cases.

Equation (14a) may be re-arranged into the form of (6a) to isolate the unit root. The resulting equation may be used in the two-part test procedure described above to perform a test of the random walk model. Fuller [20] also reports the distribution of the "t" statistic for \( \phi_1 \) when (6a) is estimated with a trend term and the true value of the trend parameter is zero, and we use his results for this test.

B. Empirical Results

The last two rows of columns 2, 3, and 4 of Table 1 contain the estimated t-values and F-ratios used to test the hypotheses \( \phi_1 = 1 \) and \( \phi_2 = \ldots = \phi_n = 0 \) in the U.S. annual data. They are very near zero and thus confirm the results of our earlier analysis.

The story changes somewhat when a time trend is added to the model. However, the Box-Pierce test still provides no evidence against the random walk hypothesis. Furthermore, the "t" statistic for \( \phi_1 \) is above (algebraically) the critical value of -3.12 for a test at the 10% confidence level regardless of which order of the autoregression is specified and so the unit root hypothesis is accepted. Finally, the F-ratio for testing \( \phi_2 = \ldots = \phi_n = 0 \) is not significant at the .25 level in the case of the AR(3) model and not significant at the 0.1 level in the case of the AR(2) model.\(^{17/}\) These results are less

\(^{17/}\)Following the usual nomenclature we will refer to autoregressive models of order \( k \) as AR(\( k \)) models.
favorable to the random walk hypothesis than those without the time trend, but they still do not indicate that it can be rejected at conventional test levels. For what it is worth, the conventional F-tests of the random walk hypothesis now indicate that it should be rejected, but as noted earlier, the distribution of the "F-ratios" is not known.

In sum, the random walk model for the real wage rate cannot be rejected in the annual data. Of course, data over so long a span suffer a number of serious problems that range from the relatively poor measurement of wages in the early years of the series to the likelihood of structural change. For this reason, we also conduct the analysis using seasonally adjusted post-war quarterly data on real hourly wages in the U.S. and the U.K. The U.S. data are for manufacturing production and non-supervisory workers. The U.K. data are for manual workers, all services and industries.\(^{18}\)

The autoregressions without time trends for the U.S. quarterly data are in columns 1-6 of Table 2. A Box-Pierce test does not reject the random walk at the .10 significance level for the random walk model without a time trend.\(^{12}\) However, for AR(1) to AR(6), the t-values to test \( \phi_1 = 0 \) are significant at the 0.01 level, and so the random walk hypothesis is rejected.\(^{20}\) On the other hand, the hypothesis that \( \phi_2 = \ldots = \phi_6 = 0 \) is accepted. In summary, the autoregressions without time trends provide reasonably clear evidence against the random walk hypothesis.

\(^{18}\) See the appendix for details.

\(^{12}\) Note that the Box-Pierce statistics for the other models without trends are all significant at the .05 level. This appears to be due to sizeable autocorrelations at the 7th and 8th lags, and we comment on this below.

\(^{20}\) The conventional F-tests of the random walk hypothesis reported in the table also support its rejection.
However, it is more difficult to reject the random walk in the regressions with time trends. The tests for a unit root and the hypothesis that all the other roots are 0 provides little evidence against the random walk hypothesis. The smallest t-value (-2.337 for AR(1)) is well above the critical value of -3.15 required to reject $\phi = 1$ at the 0.05 significance level. In addition, the F-ratio to test $\phi_2, \ldots, \phi_n = 0$ is above the critical value for a test at even the 0.25 level in only one case (the AR(5) model). Consequently, the autoregressions with the time trend included appear to support the random walk hypothesis.\(^{21}\)

The Box-Pierce statistic raises questions about these results. It has a marginal significance level of .062 in the random walk model with time trend\(^{22}\) and is significant at the .05 level for the AR(1), AR(3), AR(5), and AR(6) models with trend. The failure of the computed significance level of the Box-Pierce statistic to decline as the lag structure of the AR process for the wage is lengthened is surprising. The loss in degrees of freedom apparently outweighs the reduction in the value of the test statistic.

\(^{21}\)The F-ratios for an overall test for a random walk are significant at the .05 level for the case of the AR(2) and AR(1) models, but we give this little weight for reasons already discussed. The fact that the trend is significant when $\phi_1 = 1$ and the other coefficients are set to 0 is somewhat disturbing. It suggests the presence of a quadratic term or a structural shift in the time trend of (14a). Perhaps this is a reflection of the productivit growth slowdown in the U.S. during the 1970's. The quadratic term drops out of the autoregressive representations only if a unit root is present. It might be sensible to include quadratic terms under the alternative hypothesis. Unfortunately, in that case it is unclear how to test the hypothesis $\phi_1 = 1$.

\(^{22}\)The fact that the marginal significance levels of the Box-Pierce tests for the random walk model with and without trend rise to .184 and .296 respectively when the first two residuals (for 1948:3 and 1948:4) are dropped suggests that findings may in part be due to adjustments during the postwar years.
As it turns out, the problem is due to autocorrelations in the residuals at the 7th and 8th lags. Based on an examination of the autocorrelation of the residuals from the AR(1) model with trend, we estimated the AR(8) model with the coefficients for lags 2-6, 3-6, and 4-6 alternatively set to 0. Interestingly enough, the model with only \( w_{t-1}, w_{t-7}, \text{and } w_{t-8} \) has the lowest standard error (.06169) and highest computed marginal significance level for the Box-Pierce test (.2431). The model with \( w_{t-1} \) to \( w_{t-6} \) repressed, which is representative, is reported in the footnote below.\(^{23/}\) Neither the t-ratio to test for a unit root nor the F-ratio to test whether the other roots are 0 provide much evidence against the random walk hypothesis. Indeed they are more favorable to the random walk model than the results in Table 2. Since the properties of the forecasts from this regression are nearly identical to those from the regressions in Table 2 we do not discuss it further.\(^{24/}\)

We also investigated a number of other possibilities. The autoregressions including a trend variable were fitted to data that had not been seasonally adjusted, but with seasonal dummy variables added. This led to results very

\[
\begin{align*}
23/ (w_t - w_{t-1}) &= 0.1385 + .000045 \text{ Time} + 0.0613 w_{t-1} \\
&\quad - .105 w_{t-2} + .0351 w_{t-3} - .1824 w_{t-7} \\
&\quad + .1657 w_{t-8} \\
R^2 &= .133; \ SE = .0062; \ S.E. \ of \ implied \ forecast \ index \ w_t^* = .0096; \ Marg. \ signif. \\
level, \ Box-Pierce \ (12) &= .1407; \ t-value \ for \ test \ of \ unit \ root = -1.556; \ F-ratio \\
to \ test \ \phi_2, \ \ldots, \ \phi_8 = 0 = 1.1207.
\end{align*}
\]

\(^{24/}\) The response of \( w_t^* \) to a one unit innovation in the wage is .753 for this autoregression, which is slightly larger than the results for the other models discussed below.
similar to those in Table 2. The models were also estimated in first differences with and without a trend, and we tested the hypothesis $\phi_2 = \ldots = \phi_n = 0$ with the unit root hypothesis maintained. As before, these F tests (marginally) reject the null hypothesis at the .05 significance level when the time trend is excluded, but do not reject the random walk hypothesis at any reasonable significance level when the time trend is included. Finally, a first order moving average component was added to the third order autoregression in differences and found to be insignificant.

Considering all these results together, there is very little strong evidence against the random walk hypothesis in the U.S. quarterly data, and the weaker unit root hypothesis should probably be accepted. However, in view of the peculiar pattern of autocorrelations underlying the results for the Box-Pierce test further analysis is perhaps needed.

The results of fitting the same models used in Table 2 to quarterly data for the U.K. are reported in Table 3. The general tenor of these results is similar to those for the U.S. data, but they contain clear evidence against the random walk hypothesis. As in the U.S. case, the random walk hypothesis survives the Box-Pierce test, but now at the .20 level whether or not a time trend is included. For the models without time trends the t-values for the test of the unit root are very small in absolute value and provide little evidence against the hypothesis. However, the hypothesis that the other roots are 0 is rejected by the F-test of the hypothesis $\phi_2 = \ldots = \phi_n = 0$ for all the models except AR(2). The random walk hypothesis is also rejected in the autoregressions with time trends. The "t-test" for a unit root is barely passed at the 10% significance level, but the F-ratios indicate that the hypothesis $\phi_2 = \ldots = \phi_n = 0$
must be rejected at conventional test levels. In sum, with the U.K. data, we would firmly reject the random walk model, but accept the unit root hypothesis.

Finally, as a less formal comparison of the random walk and other forecasting models Tables 1, 2, and 3 also contain the root-mean-squared-errors (MASE) of the within sample forecasts of $w^*|y_t$. It should be noted that the same considerations of non-stationarity which invalidate the results of conventional F-tests of the random walk model may apply to comparisons of the within sample forecast errors. The results of the comparisons vary. For example, so long as no trend term is included the random walk with drift performs about as well in the U.S. annual data and in the U.K. quarterly data as does any other scheme. When trend terms are included in equations with these data, however, the random walk is a somewhat inferior forecasting device. In the U.S. quarterly data, on the other hand, the random walk is an inferior forecasting device for $w^*|y_t$ only when the trend term is not included. We conclude that the informal comparison of within sample forecast accuracy of the different models qualifies to some extent our acceptance of the random walk model in the U.S. annual data, but it adds little to the test results for the U.S. quarterly data, and is consistent with our rejection of the random walk model.

\[25\]

Using equation (5) $w^*|y_t$ is a weighted average of the future period forecasts from a given estimated model. $w^*|y_t$ is compared to the same weighted average of the realized values of future wage rates. There is inevitably some arbitrariness in the choice of index weights $\gamma_k$. We chose $m=6$ and assumed that the $\gamma_k$ follow a pattern of slow exponential decay as explained in the appendix. A rigorous basis for these choices would be desirable, and should receive further research. We consider them reasonably favorable to the intertemporal substitution hypothesis, but doubt that the results are very sensitive to them.
hypothesis in the U.K. quarterly data. The analysis also indicates that further empirical analysis with these forecasts may be sensitive to the removal of trends, and we shall therefore report results from forecasts of \( w_t^* \mid y_t \) that both include and exclude this variable.

C. Summary

Although they differ in detail, these tests provide some indication that a random walk with a drift component that is constant or obeys a trend may be a reasonably accurate scheme for forecasting aggregate real wage rates. Although far from conclusive, this implies that with complete information the deviation of an index of rational forecasts of future real wage rates from current real wage rates will possess little cyclical variability. If this is the case the aggregate unemployment function \((3a)\) will not have much explanatory power, and we turn next to a more direct exploration of this issue.

III. Wage and Unemployment Movements

As we have observed, accepting the statistical hypothesis that real wage rates may be forecasted as a random walk with drift may merely imply poor statistical discrimination. Economically significant movements in \( (w_t^* \mid y_t - w_t) \) may still exist and they may be large enough to account for the variability in measured unemployment if short-run labor supply elasticities are large enough. Likewise, even in the random walk case, when information is incomplete

\[26/\] If the drift component obeys a trend \( (w_t^* \mid y_t - w_t) \) will obey a trend in the random walk case. In fact, a trend is responsible for most of the movement in \( (w_t^* \mid y_t - w_t) \) for the U.S. quarterly data.
movements in \((w_t^*|y_t^*-u_t^*|y_{t-1})\) may also be large enough to account for the variability of unemployment.

A. Wage Variability

If we knew the value of the parameter \(a_{l1}\) in (3a) we could compute the \(R^2\) for this equation as \(R^2 = (a_{l1})^2 \frac{\text{var}(w_t^*|y_t^*-u_t^*)}{\text{var}(u_t^*)}\). Although this coefficient is not known, it seems unlikely that the short run labor supply elasticity would be larger than 2. If we also assume that \(a_{l1} = 1\) because unemployment and \(h_t^* - h_t\) are measured in the same units, then the variance in \((w_t^*|y_t^*-u_t^*)\) must be at least one-fifth as large as the variance in unemployment for the \(R^2\) in equation (3a) to be as large as .8. Likewise, if the real wage does follow a random walk and \(\theta = 1\) in (3c), then \(\sigma^2\) must be at least one-fifth as large as the variance in unemployment for the \(R^2\) in equation (3c) to be as large as .8. Although these calculations are to some extent arbitrary they provide an indication of whether the variation in the average deviation of expected future wage rates from actual wage rates is "big enough" to explain unemployment movements.

Without going into details, it is clear that, in principle, there is enough wage variability in the quarterly data for both the U.S. and the U.K. to explain the post war movements in unemployment in these countries. In the annual data for the U.S. it is less clear that this is the case. It follows, therefore, that this issue can only be resolved by fitting equations (3a) and (3c) to the data.

B. The Explanation of Unemployment

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- determinants of the Unemployment Proportion: U.K. Quarterly Data

Forecasts from AR(5) With Trend

Coefficient Estimates (t-ratios in parentheses)

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equations (3a) and (3c) to the three sets of data.\textsuperscript{27} Aside from reporting the results of fitting these equations directly, we have also reported the fit of two modifications of these equations. First, some have argued that sluggishness in the adjustment of unemployment ought not to count against the intertemporal substitution hypothesis, and so we have also included lagged terms in unemployment in the fitted versions of equations (3a) and (3c) to account for this sluggishness.\textsuperscript{28} The indicated serial correlation in the residuals of the fitted equations that do not include these lagged unemployment terms also indicates that some such modification is desirable. Second, the theoretical structure provides little guidance about the appropriate length of the time period for which the estimation of (3a) and (3c) is appropriate. Although we fit these equations to both annual and quarterly data, we have also introduced lagged values of the terms \((w^*_t y_t - w_t)\) and \((w^*_t y_t - w^*_t y_{t-1})\) into equations (3a) and (3c) as an admittedly arbitrary scheme for accounting for lags that may be due to temporal aggregation.

\textsuperscript{27} There is a potential simultaneous equations bias in these estimates if the error \(v_t\) in (3c) is correlated with the error in either the aggregate structural demand or supply functions. As things stand, however, this correlation must be attributed to an error covariance matrix that is not diagonal, because (3c) is part of a recursive system where \(v_t\) and \(h_t\) are jointly determined and the former determines \(u_t\), and not vice versa. This point is discussed in more detail and used in an alternative test of the labor market equilibrium hypothesis by Altonji.\textsuperscript{11}, \textsuperscript{27}

\textsuperscript{28} See Lucas\textsuperscript{[28]} and Sargent\textsuperscript{[19]} for models where lagged employment or unemployment play a role in a supply function such as (1). Simply adding lagged employment terms to (1) does not affect (2) as things stand, however, because they will cancel on subtraction. The justification for the inclusion of lagged unemployment values in (3a) and (3c) will therefore require some further modification of Lucas and Happing's interpretation of unemployment.
Table 4 contains a complete set of the results of fitting equations (3a) and (3c) to the annual U.S. data. In the left panel of the table we report the results when the various wage variables are generated by the AR(3) model without a trend, while the right panel reports the results when the various wage variables are generated by the AR(3) model with a trend. There are two major conclusions to be drawn from this table. First, the wage movements in equations (3a) and (3c) do not provide much help in the explanation of unemployment. The marginal significance levels of various joint hypothesis tests are listed in Table 7, and these indicate that in most cases the wage variables taken as a group do not have estimated coefficients that would be judged significantly different from zero at conventional test levels when the lagged unemployment terms are included in the equations. Second, the deviation \( \ln y_t - \ln v_t \) and its lagged values typically have negative estimated coefficients, which is contrary to what is expected with the intertemporal substitution hypothesis. In sum, the annual U.S. data provide no support for the intertemporal substitution explanation for movements in unemployment.

The quarterly data give results that are more ambiguous. The results in Tables 5 and 6 use the AR(5) model with a trend to generate the wage variables, and we report only these results since, as can be seen from the significance tests in Table 7, they are more favorable to the intertemporal substitution hypothesis than the results based on the AR(5) model without a trend. Column 6 of Table 5 provides the results of fitting equation (3c) with the lagged unemployment terms included. The estimate of \( a_{15} \) is essentially
Table 7

Marginal Significance Levels for Tests of the Determinants of Unemployment

Joint Tests of the Effects of
$w_t^* | y_t - u_t$ and $(w_t^* | y_t - u_t^* | y_{t-1})$
on Unemployment

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<th>Unemployment</th>
<th>Unemployment Conditional on $u_{t-1}$, $u_{t-2}$</th>
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<tr>
<td></td>
<td>Forecasts</td>
<td>Forecasts w/o Trend</td>
</tr>
<tr>
<td>U.S. Annual</td>
<td>0.1669</td>
<td>0.0200</td>
</tr>
<tr>
<td>U.S. Quarterly</td>
<td>0.0036</td>
<td>0.0001</td>
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<tr>
<td>U.K. Quarterly</td>
<td>0.0101</td>
<td>0.0007</td>
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Joint Tests of the Effects of Current and Lagged Values of
$w_t^* | y_t - u_t$ and $(w_t^* | y_t - u_t^* | y_{t-1})$
on Unemployment

<table>
<thead>
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<td>Forecasts</td>
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</tr>
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<td>U.S. Annual</td>
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<td>U.S. Quarterly</td>
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<td>U.K. Quarterly</td>
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zero and poorly determined, as might be expected if \( w^*_t | y_t - w_t \) did not vary.\(^{29}\) The estimate of \( \delta \) is -.16, however, and significantly different from zero. If we take \( \delta = 1 \), as indicated by the microeconomic data, this gives a labor supply elasticity of only .16. Although this is consistent with many cross-sectional estimates of long run supply elasticities, it suggests that only a small part of the time-series movements in unemployment can be attributed to intertemporal substitution. The results in Column (8) are perhaps more favorable to the intertemporal substitution hypothesis. The sum of the current and lagged values of \( w^*_t | y_t - w_t \) is still negligible, but the sum of the coefficients on the current and lagged forecast revisions is -.83. This implies a labor supply elasticity of .83, but this parameter is not estimated with enough precision for it to be judged significantly different from zero at conventional test levels.

As reported in column 8 of Table 6 the U.K. quarterly data give results that are similar to the U.S. quarterly data when the lagged wage and unemployment terms are included in equation (3c). As in the U.S. quarterly data, the coefficients on the current and lagged values of \( w^*_t | y_t - w_t \) are negligible. Although we have no estimate of \( \delta \) for the U.K., if we assume \( \delta = 1 \) as for the U.S., the estimated supply elasticity (from the sum of the coefficients on the current and lagged values of \( (w^*_t | y_t - w^*_t | y_{t-1}) \)) is 1.06 and significantly different from zero at conventional test levels. However, none of the other results in Table 6 give elasticities as large as this, and even in column 8

\(^{29}\) As noted above, for the U.S. quarterly data \( w^*_t - w_t \) shows little cyclical variation but does decline over time due to a trend.
a joint test of the hypothesis that all the wage coefficients are zero has a marginal significance level of around .30.

In sum, the U.S. annual data provide little support for the inter-temporal substitution explanation for movements in unemployment. The U.S. and U.K. quarterly data likewise provide little support for an intertemporal substitution hypothesis based on complete information, but they do provide some limited support for a model based on incomplete information. Estimates of important parameters are very imprecise, however, and a number of arbitrary assumptions about the lagged effects of wage variations are necessary to find this support.

IV. Conclusion

We have found empirically that it is very difficult to attribute movements in unemployment to aggregate deviations in expected future real wage rates from current real wage rates. In fact, these results are not very different from others that have appeared in the literature, such as Sargent's [32], [33]. The explanation for this finding in the case where workers are assumed to have complete information about the current aggregate wage appears to be that the time series process of the aggregate real wage is close to a random walk with drift. The result is that rational forecasts of future real wage rates differ by a constant from current real wage rates and there is very little variation in these deviations with which to explain unemployment.

The available evidence from longitudinal data suggests that the "noise" in individual real wage rates is large enough that the current aggregate wage may be effectively unknown to individual workers. If this is the case rational forecasts by individual workers will lead to correlation between aggregate
unemployment and aggregate forecast errors or "surprises" in the real wage. In the annual data we find little evidence of this correlation. Although we do find some weak evidence for it in the quarterly data in both the U.S. and the U.K., most of the observed variation in post-war unemployment remains unexplained or attributed to its own past values.

We have pointed out many limitations to these results and they leave open a considerable agenda for further research. For one thing, we have followed Neftci and Sargent in assuming that a simple autoregressive structure provides a reasonable forecast device for future wage rates. A richer structural labor market model in which expectations of future wage rates are fully rational would no doubt produce a different scheme and the development of such a model will have to be an important part of any fair test of the labor market equilibrium hypothesis.

The finding that aggregate real wage rates are well explained by their own past values and perhaps even follow a random walk invites speculation about the kind of aggregate labor market model that is consistent with this stylized fact. Our own work suggests that the empirical connection between microeconomic movements in wages and prices and the macroeconomic variability in these quantities has not been fully exploited, and that further work along these lines may be useful.
APPENDIX

This appendix describes the data used in the study and the calculation of the permanent wage indices.

I. U.S. Quarterly Data

a) Real Wage Rates: The quarterly real wage rate is for seasonally adjusted straight time gross hourly earnings for all manufacturing industries, production and nonsupervisory workers, 1947.1 to 1978.4.\(^{30/}\) They were obtained by dividing the monthly series for average hourly gross earnings per production or nonsupervisory worker, excluding overtime (U.S. Dept. of Commerce [39], pp. 81, 251 and U.S. Dept. of Labor [40] (1978) pg. 93 and (1979) pg. 91) by the Consumer Price Index (U.S. Dept. of Commerce [39], pp. 43, 229 and Economic Statistics Bureau of Washington D.C. [17], pp. 100-101). Since the historical series on the Consumer Price Index was discontinued in June 1978, the series was extended via a ratio link to the new series in that month. The monthly data was aggregated into a quarterly series for the real wage. Finally, the quarterly series was seasonally adjusted using the method of ratio of the series to a moving average.

b). Unemployment Rates: The unemployment rate is all unemployed civilian workers as a fraction of the civilian labor force, seasonally adjusted. (U.S. Dept. of Commerce ([39], pp. 69, 245) and Council of Economic Advisors [10], pg. 216.)

\(^{30/}\) The estimation period is 1948.3 to 1978.4 since observations are lost in estimation due to the lagged values of dependent variables and it was desired to estimate the models over the same sample.
II. U.S. Annual Data

a) **Real Wage Rate:** The real wage rate is a series on real compensation per manhour for the whole economy. It was produced by Altonji [2] in an attempt to extend the sample utilized by Lucas and Rapping to 1976. It equals compensation of employees (U.S. Dept. of Commerce, [37], pp. 194-197 and [38], pg. 46) divided by the product of full time equivalent employees, [37], pp. 206-209 and [38], pg. 47) the GNP implicit price deflator ([37], pp. 264, 265 and [38], p. 349) and estimates of annual hours per worker. In the absence of a consistent series from 1929-1976 on annual hours per worker for the whole economy, it was necessary to construct a series from Christensen and Jorgenson's ([8], pg. 89) series on hours for private sector employees 1929-1969, and data on annual hours per worker for the whole economy, 1929, 1940-1941, 1947-1976 prepared by E.F. Denison, which he kindly provided prior to publication. The relationship between the two series was estimated for the years 1929, 1940-41 and 1947-1969 using the method of maximum likelihood. In specifying the likelihood function it was assumed that Deninson's series is a linear function of Christensen and Jorgenson's series plus a constant and a normally distributed first order autoregressive error, with gaps in the sample taken into account. Maximum likelihood estimates of Deninson's series were then calculated and used to fill the gaps in his data. For further details see Altonji [2]. Finally, since we did not wish to drop the early years of the Great Depression from the sample, it was necessary to obtain estimates of real wage for 1926-1928. These were obtained by joining Lewis' data [25], p. 202 for these years to the data for 1929-1976 with a ratio link in 1929. In practice, dropping the observations made little difference in the estimates reported in Table 1.
b) Annual Unemployment Rate: The series is unemployment, all civilian workers as a fraction of the civilian labor force. (Lebergott [24], Council of Economic Advisors [10], p. 217).

III. United Kingdom Quarterly Data


b) Unemployment: The unemployment rate is the fraction of persons registered as unemployed divided by all employees. For 1948:2 to 1964:4 it is obtained by aggregating and then seasonally adjusting the monthly data from Department of Employment and Productivity [13], pp. 330-332. For 1965:1-1974:3, the seasonally adjusted quarterly data reported in Central Statistical Office ([7], p. 91) are used. The sample ends at 1974:3 due to missing data for 1974:4 and 1976:4.

IV. Computation of the Expected Future Wage Index

\[ w_{t+k} | x_t \], the forecast of \( w_{t+k} \) conditional on the values of the wage at \( t \) and earlier periods, was generated recursively from the estimated auto-regressions reported in Table 1 for U.S. annual data, and Tables 2 and 3 for U.S. and U.K. quarterly data. Forecasts →
from the AR(3) model were used for the annual data and the AR(5) models for the quarterly. This choice is not based on a formal model selection criteria and further analysis is needed. Conditional on the assumption that the models chosen are correct, the results are minimum mean square error forecasts, $w_t^*$ was computed as a linear function of the forecasts for future periods according to (5) above:

$$w_t^* = \sum_{k=1}^{m} \gamma_k ( \hat{w}_{t+k} )$$

Since $w_t^*$ is a linear function of the forecasts for future periods, it is the minimum mean square error forecast of the corresponding linear function of the future observations.\(^{31/}\)

The weights $\gamma_k$ are assumed to decline geometrically according to the formula

$$\gamma_k = \beta^{k-1}/[1 - \beta^m / (1 - \beta)] .$$

The term in brackets normalizes the $\gamma_k$'s to sum to one. $\beta$ and $m$ were set to .8138 and 30 (respectively) for the annual data and to .95 and 32 for the quarterly data. The implied annual rates of decline in the weights on future wages is the same in the quarterly and annual calculations. The weight in $w_t^*$ of the forecast of the wage eight years in the future is .238\(^{32/}\) of the weight of the forecast for the wage one year ahead.

\(^{31/}\)See Box and Jenkins [5], p. 128.

\(^{32/}\)0.238 = \{(.95^{28} + .95^{29} + .95^{30} + .95^{31})/41 / (1 + .95 + .95^2 + .95^3)/4\).
This number seems to us to be large. It is the ratio of the elasticity of current labor supply with respect to an expected change in the wage 8 years in the future to the elasticity with respect to the change one period ahead.

The procedure described above was used to generate forecasts of $v_t^t | y_{t-1}$. 

REFERENCES


[38] _______. Survey of Current Business (July 1977), Washington, D.C.
