AN EFFICIENCY WAGE APPROACH TO RECONCILING THE WAGE CURVE AND THE PHILLIPS CURVE*

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Abstract

This study develops an efficiency wage model that generates a wage curve at the regional level and a Phillips curve at the national level, under the assumption that workers' efficiency depends on both regional and aggregate labor market conditions. An equation relating wages to unemployment and lagged wages is derived from the profit-maximizing behavior of firms, and it is demonstrated that the coefficient on lagged wages is less than 1 with regional data but equals 1 with aggregate data. In addition, there is an equilibrium relationship between unemployment and wages at the regional level, but not at the aggregate level.

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1. Introduction

The Phillips curve, which is a relationship between unemployment and the rate of change in wages or prices, has been an integral part of macroeconomic modeling since the publication of Phillip's (1958) seminal paper. More recently, Blanchflower and Oswald (1994) argue that the relationship between unemployment and wages can be more accurately described by the wage curve, which is a relationship between unemployment and the level of real wages. Using data from many countries, Blanchflower and Oswald regress the log of the wage on the log of the regional and/or industry unemployment rate, and they find a negative relationship between unemployment and real wages. In addition, when their regressions include the lagged wage, its coefficient is generally small and insignificant.[1]

The Phillips curve and the wage curve differ in several respects. First, because the Phillips curve is a relationship between wage inflation and the unemployment rate, lagged wages should enter with a coefficient of 1 when current wages are regressed on unemployment and lagged wages. On the other hand, the wage curve literature predicts that this regression should yield a coefficient on lagged wages that is significantly less than 1. Second, Phillips curves are generally estimated with macroeconomic time-series data, while wage curves are estimated with pooled cross-section time-series data, with the dependent variable being either individual wages or average wages in a region or industry.[2] Third, according to Blanchflower and Oswald (1995, p. 164), "the Phillips curve was proposed as a disequilibrium adjustment mechanism. … In our conception, the wage curve is an equilibrium locus that is a description neither of inherently temporary phenomena nor of transitory dynamics."

This study develops a model of wage setting under the assumptions that firms pay efficiency wages, that workers have imperfect information about wages at other firms, and that workers' efficiency depends on both regional and aggregate labor market conditions. It is demonstrated that the relationship between current wages, unemployment, and lagged wages has the characteristics of a wage curve when a regression is estimated with pooled microeconomic data, and has the characteristics of a Phillips curve when estimated with aggregate time-series data.

The model is first developed for a local labor market. An equation is derived that relates regional wages to regional unemployment, lagged regional wages, aggregate unemployment, and expectations of aggregate wages. The coefficient on regional unemployment is negative, and the coefficient on lagged regional wages lies between 0 and 1, both of which are in agreement with the wage curve literature. In addition, the analysis provides a potential explanation for the finding that the log of regional wages is more closely related to the log of regional unemployment than to its level.

The model is subjected to a demand shock or series of demand shocks, and theoretical expressions are obtained for the paths that regional wages and unemployment follow over time.[3] It is demonstrated that demand shocks have long-term effects on both wages and unemployment, so there is a long-run equilibrium relationship between these variables. When numerical values are chosen for the model's parameters, the long-run elasticity of wages with respect to unemployment is generally close to values that have been empirically estimated, and this elasticity is relatively invariant to changes in most of the parameters.

As workers place more weight on local labor market conditions (relative to aggregate conditions), the coefficient on lagged wages rises. In the limiting case in which the local labor market is assumed to be the entire economy, this coefficient equals 1. This means that the rate of change in wages depends on the level of unemployment, so that the aggregate economy is characterized by a Phillips curve. This Phillips curve is a disequilibrium relationship, as aggregate unemployment eventually returns to its natural rate.

After a single regional economy and the aggregate economy are analyzed separately, simulations are performed for a multiregional economy in which there are aggregate and region-specific demand shocks in each period. In a pooled regression of regional wages on lagged wages and regional unemployment, the coefficient on lagged wages is less than 1. However, when aggregate data are created by averaging regional data, the coefficient on lagged wages equals 1 in the aggregate wage equation. Thus, the same data yield a wage curve at the local level and a Phillips curve at the aggregate level, showing that there is no contradiction between the wage curve and the Phillips curve.

The reason why regional wage dynamics and aggregate wage dynamics differ is that, in modeling a regional economy, it is assumed that workers' efficiency depends on labor market conditions both inside and outside of the economy being modeled. In contrast, when the aggregate economy is considered, efficiency does not depend on labor market conditions outside the economy.

2. Relationship of the present study to past work on the wage curve and Phillips curve

The present study differs in several important respects from previous research on the wage and Phillips curves. Many studies have developed models of either the wage curve or the Phillips curve. Blanchflower and Oswald (1994) show how a wage curve relationship can be obtained from models involving contracts, efficiency wages, and bargaining. Models of the Phillips curve have been developed by Roberts (1995) and Galí and Gertler (1999) with staggered price contracts, Blanchard and Katz (1999) with adaptive expectations about reservation wages, and Mankiw and Reis (2002) with sticky information. However, none of these studies considers the wage curve and the Phillips curve in a single model, so they do not explain why economists have found different wage dynamics at the national and regional levels.[4]

The present study develops a model, derived from the profit-maximizing behavior of firms, which can explain both the wage curve and the Phillips curve.[5] When workers' efficiency depends on labor market conditions both inside and outside of the economy being considered, the relationship between wages and unemployment looks like a wage curve. On the other hand, the relationship looks like a Phillips curve when their efficiency depends on labor market conditions only within the economy being considered. Thus, this study provides explanations for why the wage–unemployment relationship appears to differ qualitatively between the regional and national levels and for why there is an equilibrium relationship for regional economies but not for the aggregate economy.

Blanchard and Katz (1999) and Montuenga-Gómez and Ramos-Parreño (2005) discuss the possibility that workers' behavior may be affected by both regional and national labor market conditions. However, these studies do not develop formal models incorporating this assumption and do not use this assumption to show how a wage curve at the local level is compatible with a Phillips curve at the national level.

The results of Galí and Gertler (1999) suggest that wage behavior is an important determinant of price dynamics. They find that a Phillips curve model in which price inflation depends on expectations of future marginal cost (where marginal cost is measured by labor's share of national income) outperforms a conventional sticky price model in which inflation depends on the output gap. Since the present model explains the determinants of wages, it may be able to explain price inflation better than Phillips curve specifications that relate inflation to the output gap.[6]

In addition, the present study differs from previous work by explicitly deriving expressions for the paths followed by wages and unemployment in response to shocks. Deriving these expressions makes it possible to demonstrate that wage curve and Phillips curve relationships are obtained in a model in which wages and unemployment are both endogenous, and it enables wage and unemployment dynamics to be simulated in a multiregional economy.

3. Assumptions

In deriving the model, the following assumptions are made:

1. Workers' efficiency (e) depends on the ratio of their current wage to their expectations of wages at other firms and on the unemployment rate, so that

$$e = e[W_t / \Omega_t, u_t], \qquad \text{with } e_W > 0, \quad e_u > 0, \quad e_{WW} < 0, \quad \text{and } e_{Wu} < 0,$$ [7]

   where W_t is a worker's current wage, Ω_t denotes workers' expectations of average wages (to be defined below), and u_t is the unemployment rate. Explanations for why productivity may depend on wages and unemployment include the shirking model of Shapiro and Stiglitz (1984); the gift-exchange/fair wage models of Akerlof (1982, 1984) and Akerlof and Yellen (1990); the labor turnover models of Stiglitz (1974), Schlicht (1978), and Salop (1979); and the adverse selection model of Weiss (1980). The function $e[W_t / \Omega_t, u_t]$ can be viewed as incorporating all of these explanations.

2. When a regional economy is modeled, workers' efficiency depends both on regional and aggregate labor market conditions, since both regional and aggregate conditions may affect the cost of job loss, the satisfaction workers feel towards their employer, and the quit propensity of workers. Thus, efficiency depends both on the ratio between a

worker's wage and a weighted average of regional and aggregate wages, and on a weighted average of the regional and aggregate unemployment rates. In particular, it is assumed that

$$\Omega_t = \left(\Omega_t^R\right)^{\nu_1}\left(\Omega_t^N\right)^{1-\nu_1}, \qquad \text{and}$$

$$u_t = \nu_2 u_t^R + (1-\nu_2)u_t^N,$$ [8]

where Ω_t^R and Ω_t^N represent workers' expectations of average regional and national wages, ν_1 is the weight they place on regional wages (relative to aggregate wages) in comparing their own wages to a benchmark, u_t^R and u_t^N are the regional and national unemployment rates, and ν_2 is the weight workers place on regional unemployment in making decisions that affect their efficiency.

The assumption that efficiency depends on labor market conditions both inside and outside of the regional economy is supported by previous research. Ziliak et al. (1999), Jimeno and Bentolila (1998), Buettner (1999), and Elhorst et al. (2005) find that workers' wages depend on wages and/or unemployment in both the regional and national economies.[9] In addition, Morrison et al. (2006) show that quits (which may negatively affect efficiency) in local labor markets in New Zealand respond to wages in other regions of the country. Furthermore, U.S. Census Bureau data indicate that workers are mobile across regions, and Blanchard and Katz (1992) and Kennan and Walker (2003) find that migration depends on relative labor market conditions.[10] The evidence that workers are geographically mobile and that migration depends on relative economic conditions suggests that workers' behavior is affected by both regional and aggregate conditions.

3. In the short run, workers may have incomplete information on current wages at other firms and may use information on lagged average wages to help predict current average wages.[11] The fact that expectations of current average wages depend partly on lagged average wages means that workers' expectations of average wages can be viewed as a mixture of rational and adaptive expectations, so that

$$\Omega_t^R = \left(\overline{W}_t^{\,R}\right)^{\omega}\left(\overline{W}_{t-1}^{\,R}\right)^{1-\omega} \quad \text{and} \quad \Omega_t^N = \left(\overline{W}_t^{\,N}\right)^{\omega}\left(\overline{W}_{t-1}^{\,N}\right)^{1-\omega},$$

where $\overline{W}^R$ represents average wages in the workers' region, $\overline{W}^N$ represents average wages in the aggregate economy, and ω measures the degree to which expectations are unbiased.[12]

While much work in macroeconomics assumes that expectations are rational (i.e., unbiased), empirical evidence and theoretical considerations suggest that expectations may be better described as a mixture of rational and adaptive expectations. Economists who have examined survey forecasts of inflation generally find that inflationary expectations do not satisfy the criteria for completely rational expectations.[13] From a theoretical standpoint, Conlisk (1988) argues that if it is costly to form accurate expectations of next period's price level, then optimal forecasts may be a weighted average of an unbiased estimate obtained from agents' costly optimization activities and a "free estimator," which may be determined from an adaptive expectations process. In addition, the assumption that expectations are not completely rational is made in the Phillips curve models of Blanchard and Katz (1999) and Mankiw and Reis (2002).[14]

4. In the product market, each firm faces a downward-sloping demand curve of the following form:

$$Q = \theta * P^{-\gamma},$$

where $\theta *$ is the level of product demand, and γ is the price elasticity of demand. Accordingly, P can be expressed as

$$P = \theta Q^{-\frac{1}{\gamma}}, \qquad \text{where } \theta = \theta *^{\frac{1}{\gamma}}.$$

5. Firms produce output with the Cobb-Douglas production function,

$$Q_t = A_t L_t^{\phi} K_0^{1-\phi} e[W_t / \Omega_t, u_t]^{\phi},$$

where technology (A) is exogenous and capital is fixed at K_0.

6. Labor supply in each region is inelastic and equals N times the number of firms. Parameters are chosen so that there is excess supply of labor in each region. It should be noted that assuming a positive relationship between wages and efficiency does not guarantee that there will be excess supply of labor. Suppose each firm faces an upward-sloping labor supply curve, in which labor supply equals N when its wage equals the regional average. A firm operates to the left of its labor supply curve (i.e., pays an efficiency wage) if the elasticity of output with respect to the wage, calculated at the market-clearing wage, exceeds the elasticity of output with respect to employment. Otherwise, it operates on its labor supply curve. Parameters are chosen so that firms maximize profits by paying efficiency wages, so wages (W) and employment (L) are determined by differentiating the profit function with respect to both W and L.

Given these assumptions, profits in each period are

$$\Pi_t = P_t Q_t - W_t L_t - rK_0 = \theta_t \left[A_t L_t^{\phi} K_0^{1-\phi} e[W_t / \Omega_t, u_t]^{\phi}\right]^{\frac{\gamma-1}{\gamma}} - W_t L_t - rK_0 . \qquad (1)$$

4. A model of wage behavior at the local level

This section develops a model of wage setting in a regional labor market under the assumption that workers' efficiency depends on both local and aggregate labor market conditions (i.e., $0<\nu_1<1$ and $0<\nu_2<1$). This model is used to determine the effect of regional unemployment and lagged regional wages on current regional wages, to determine the paths followed by wages and unemployment in response to demand shocks, and to derive an expression for the long-run wage curve elasticity. In Section 5, numerical values are chosen for the model's parameters, allowing wage curve coefficients to be calculated.

The profits of a representative firm are given by equation (1). Differentiating this equation with respect to L_t and setting the derivative equal to 0 yields

$$\frac{d\Pi_t}{dL_t} = 0 = \frac{\phi(\gamma-1)}{\gamma} \theta_t A_t^{\frac{\gamma-1}{\gamma}} L_t^{\frac{\phi(\gamma-1)}{\gamma}-1} K_0^{\frac{(1-\phi)(\gamma-1)}{\gamma}} e[W_t / \Omega_t, u_t]^{\frac{\phi(\gamma-1)}{\gamma}} - W_t ,$$

so that

$$L_t = W_t^{\frac{\gamma}{\phi(\gamma-1)-\gamma}} \left(\frac{\gamma}{\phi(\gamma-1)}\right)^{\frac{\gamma}{\phi(\gamma-1)-\gamma}} \theta_t^{-\frac{\gamma}{\phi(\gamma-1)-\gamma}} A_t^{-\frac{\gamma-1}{\phi(\gamma-1)-\gamma}} K_0^{-\frac{(1-\phi)(\gamma-1)}{\phi(\gamma-1)-\gamma}} e[W_t / \Omega_t, u_t]^{-\frac{\phi(\gamma-1)}{\phi(\gamma-1)-\gamma}} . \qquad (2)$$

The other first-order condition is

$$\frac{d\Pi_t}{dW_t} = 0 = \frac{\phi(\gamma-1)}{\gamma} \theta_t A_t^{\frac{\gamma-1}{\gamma}} L_t^{\frac{\phi(\gamma-1)}{\gamma}} K_0^{\frac{(1-\phi)(\gamma-1)}{\gamma}} e[W_t / \Omega_t, u_t]^{\frac{\phi(\gamma-1)}{\gamma}-1} \frac{e_W[W_t / \Omega_t, u_t]}{\Omega_t} - L_t . \qquad (3)$$

If (2) is substituted into (3), the following condition, which is analogous to the Solow (1979) condition, is obtained:

$$W_t e[W_t / \Omega_t, u_t]^{-1} e_W [W_t / \Omega_t, u_t] \frac{1}{\Omega_t} = 1. \qquad (4)$$

Totally differentiating equation (4), dividing it by the original equation, and substituting $(W_t / \Omega_t) = ee_W^{-1}$ (from equation 4) yields

$$0 = \frac{e_{WW} e}{e_W^2} \hat{W}_t - \frac{e_{WW} e}{e_W^2} \hat{\Omega}_t + \left[\frac{e_{Wu}}{e_W} - e^{-1} e_u \right] du_t, \qquad (5)$$

where $\hat{W}_t = dW_t / W_t$ and $\hat{\Omega}_t = d\Omega_t / \Omega_t$. Equation (5) is a relationship between percentage deviations in W_t, percentage deviations in Ω_t, and absolute deviations in u_t from their initial equilibrium values. (In this study, variables with "^"'s over them represent percentage deviations from steady-state values.) By making the substitutions $\hat{\Omega}_t = \nu_1 \hat{\Omega}_t^R + (1 - \nu_1) \hat{\Omega}_t^N$, $du_t = \nu_2 du_t^R + (1 - \nu_2) du_t^N$, and $\hat{\Omega}_t^R = \omega \hat{W}_t + (1 - \omega) \hat{W}_{t-1}$,[15] equation (5) becomes

$$\hat{W}_t = \frac{\nu_2 [e^{-1} e_W e_u - e_{Wu}]}{e_{WW} ee_W^{-1} (1 - \nu_1 \omega)} du_t^R + \frac{\nu_1 (1 - \omega)}{1 - \nu_1 \omega} \hat{W}_{t-1} + \frac{1 - \nu_1}{1 - \nu_1 \omega} \hat{\Omega}_t^N + \frac{(1 - \nu_2)[e^{-1} e_W e_u - e_{Wu}]}{e_{WW} ee_W^{-1} (1 - \nu_1 \omega)} du_t^N. \qquad (6a)$$

If the first term on the right-hand side is multiplied and divided by u_t^R, and if $\hat{u}_t^R$ is defined as du_t^R / u_t^R, then the wage equation can also be expressed as

$$\hat{W}_t = \frac{\nu_2 [e^{-1} e_W e_u - e_{Wu}] u_t^R}{e_{WW} ee_W^{-1} (1 - \nu_1 \omega)} \hat{u}_t^R + \frac{\nu_1 (1 - \omega)}{1 - \nu_1 \omega} \hat{W}_{t-1} + \frac{1 - \nu_1}{1 - \nu_1 \omega} \hat{\Omega}_t^N + \frac{(1 - \nu_2)[e^{-1} e_W e_u - e_{Wu}]}{e_{WW} ee_W^{-1} (1 - \nu_1 \omega)} du_t^N. \qquad (6b)$$

In equations (6a) and (6b), the coefficient on regional unemployment is negative. In addition, the coefficient on lagged regional wages is between 0 and 1, which means that a regional economy is characterized by a wage curve rather than by a Phillips curve.

Equation (6a) is a relationship between the percentage deviation in wages and the absolute deviation in unemployment from their initial equilibrium values, while (6b) is a relationship between the percentage deviation in wages and the percentage deviation in unemployment. Thus, the first equation is equivalent to a regression of the log of wages on the level of unemployment, while the second is equivalent to a regression of the log of wages on the log of unemployment, as wage curves are generally estimated.

Whether equation (6a) or (6b) provides a better model for empirical estimation depends on whether the coefficient on du_t^R (in 6a) or the coefficient on $\hat{u}_t^R$ (in 6b) is less affected by changes in the local unemployment rate. It is quite plausible that the coefficient on $\hat{u}_t^R$ is less affected by changes in u^R, even though u^R appears in the numerator of it. A rise in u^R may reduce ν_1 and ν_2, since individuals living in areas with high unemployment may become more willing to move to another labor market, and may therefore become more concerned with aggregate labor market conditions (relative to local conditions). If the effect of unemployment on ν_1 and ν_2 is large enough, then changes in local unemployment may have less effect on the coefficient on $\hat{u}_t^R$ than on the coefficient on du_t^R. Evidence for an inverse relationship between u^R and ν_2 is found in Longhi et al. (2006), as their results indicate that local wages in Germany respond more to unemployment in nearby regions as local unemployment increases. Thus, this analysis provides a possible explanation for why researchers have found that a log-log specification fits the data better than a log-level specification. This issue is explored further in Section 7.[16]

The model developed in this section can be used to determine the paths followed by regional wages and unemployment in response to demand shocks. There are three reasons for calculating the response of these variables to demand shocks. First, equations (6a) and

(6b) implicitly treat current regional wages as the dependent variable and regional unemployment and lagged regional wages as independent variables. Determining paths for wages and unemployment and using these expressions as data in a regression verifies that the same coefficients are obtained in a model in which these three variables are endogenously determined from their response to exogenous demand shocks. Second, determining paths for wages and unemployment allows us to examine the long-run responses of these variables to shocks. Third, the equations for wages and unemployment derived in this section are used in simulations of a multiregional economy in Section 7.

The regional unemployment rate is described by the equation,

$$u_t^R = \frac{N - L_t}{N}. \tag{7}$$

Letting $s_L = L^* / N$ (where L^* is the equilibrium value of L), du_t^R can be approximated by

$$du_t^R = \frac{-dL_t}{N} = \frac{-dL_t}{(L^* / s_L)} \approx -s_L \hat{L}_t. \tag{8}$$

Appendix A derives expressions for wages and unemployment as functions of the variables that are exogenous to a regional labor market. The equation for wages is

$$\begin{aligned}\hat{W}_t &= \frac{1}{1+\alpha(1-\nu_1\omega)}\sum_{j=0}^{\infty}\mu^j\hat{\theta}_{t-j} + \frac{\gamma-1}{\gamma[1+\alpha(1-\nu_1\omega)]}\sum_{j=0}^{\infty}\mu^j\hat{A}_{t-j} \\ &\quad + \frac{\alpha(1-\nu_1)}{1+\alpha(1-\nu_1\omega)}\sum_{j=0}^{\infty}\mu^j\hat{\Omega}_{t-j}^N + (1-\nu_2)\frac{\phi\gamma-\phi-\gamma}{s_L\nu_2\gamma[1+\alpha(1-\nu_1\omega)]}\sum_{j=0}^{\infty}\mu^j du_{t-j}^N,\end{aligned} \tag{9}$$

where

$$\alpha = \frac{e_{WW}ee_W^{-1}\eta}{s_L\nu_2\gamma\left(e^{-1}e_We_u - e_{Wu}\right)} - \frac{\phi(\gamma-1)}{\gamma},$$

$$\eta = \phi\gamma - \phi - \gamma - \phi(\gamma - 1)e^{-1}s_L \nu_2 e_u < 0,$$ and

$$\mu = \frac{\nu_1 \alpha(1-\omega)}{1+\alpha(1-\nu_1\omega)}.$$

In addition, the unemployment rate can be expressed as,

$$du_t^R = -\frac{s_L}{\eta}\Big[[\gamma - \phi(\gamma-1)(1-\nu_1\omega)]\hat{W}_t + \nu_1\phi(\gamma-1)(1-\omega)\hat{W}_{t-1} + \phi(\gamma-1)(1-\nu_1)\hat{\Omega}_t^N - \gamma\hat{\theta}_t - (\gamma-1)\hat{A}_t - \phi(\gamma-1)(1-\nu_2)e^{-1}e_u du_t^N\Big]. \tag{10}$$

We now consider the effects of two types of regional demand shocks on the behavior of wages and unemployment over time (with technology, wages in other labor markets, and unemployment in other labor markets held constant). The first type of demand shock is a series of stochastic shocks starting in period 1. It is assumed that $\hat{\theta}_t = 0$ for $t \le 0$, and that $\theta_t = \theta_{t-1} + \varepsilon_t$ for $t \ge 1$, where ε_t is a random error with a mean of 0. Appendix B demonstrates that the paths of wages and unemployment in response to a series of stochastic demand shocks are

$$\hat{W}_t = \frac{1}{1+\alpha(1-\nu_1)}\sum_{i=1}^{t}\varepsilon_i(1-\mu^{t-i+1}),\quad \text{and} \tag{11a}$$

$$du_t^R = z_1\sum_{i=1}^{t}\varepsilon_i + z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-i}, \tag{11b}$$

where

$$z_1 = \frac{s_L(1-\nu_1)[\alpha\gamma + \phi(\gamma-1)]}{[1+\alpha(1-\nu_1)]\eta} < 0,$$ and

$$z_2 = \frac{s_L(1-\omega)\nu_1[\alpha\gamma + \phi(\gamma - 1)]}{[1+\alpha(1-\nu_1)][1+\alpha(1-\nu_1\omega)]\eta} < 0.$$

The second type of shock is a one-time permanent shock to demand at time t=1, such that $\hat{\theta}_t = 0$ for $t \le 0$ and $\hat{\theta}_t = S$ for $t \ge 1$. This is a special case of stochastic demand shocks in which $\varepsilon_1 = S$, and $\varepsilon_t = 0$ for $t \ge 2$. Thus,

$$\hat{W}_t = \frac{1-\mu^t}{1+\alpha(1-\nu_1)} S, \qquad \text{and} \tag{12a}$$

$$du_t^R = (z_1 + z_2 \mu^{t-1}) S\,. \tag{12b}$$

These expressions for wages and unemployment from periods 1 through T are treated as data in the regression,

$$\hat{W}_t = \hat{\beta}_1 du_t^R + \hat{\beta}_2 \hat{W}_{t-1} + \varepsilon_t\,. \tag{13}$$

Since $\hat{W}_t$ and $\hat{W}_{t-1}$ represent percentage deviations from steady state values and du_t^R represents absolute deviations, equation (13) is equivalent to a regression in levels of the form $\ln(W_t) = \alpha + \hat{\beta}_1 u_t^R + \hat{\beta}_2 \ln(W_{t-1}) + \varepsilon_t$.[17] With both types of demand shocks, Appendix C demonstrates that

$$\hat{\beta}_1 = \frac{\nu_2[e^{-1}e_W e_u - e_{Wu}]}{e_{WW} e e_W^{-1}(1-\nu_1\omega)} < 0\,, \qquad \text{and} \tag{14a}$$

$$\hat{\beta}_2 = \frac{\nu_1(1-\omega)}{1-\nu_1\omega} < 1\,. \tag{14b}$$

When the regression equation is $\hat{W}_t = \hat{\beta}_1^* \hat{u}_t^R + \hat{\beta}_2 \hat{W}_{t-1} + \varepsilon_t$, $\hat{\beta}_2$ is the same as before, but $\hat{\beta}_1^*$ is

$$\hat{\beta}_1^* = \frac{\nu_2 [e^{-1} e_W e_u - e_{Wu}] u^R}{e_{WW} e e_W^{-1} (1 - \nu_1 \omega)} < 0 . \tag{14c}$$

The coefficient on lagged regional wages and the coefficients on regional unemployment (expressed either as absolute deviations or percentage deviations) are the same as in equations (6a) and (6b). Thus, identical coefficients are obtained if current wages are treated as endogenous and unemployment and lagged wages are treated as exogenous or if all three variables are viewed as being endogenously determined by the economy's transition path following a demand shock.

These coefficients are obtained from a model that considers only a single regional economy, whereas wage curves are generally estimated with pooled data from multiple regions of a country. However, Section 7 demonstrates that the same coefficients are obtained in a multiregional economy.

In the long-run (i.e., as $t \to \infty$), a permanent demand shock raises wages by $S/[1 + \alpha(1 - \nu_1)]$ and lowers unemployment by $z_1 S$. Thus, there is a long-run equilibrium relationship between these variables, or a wage curve. The long-run elasticity of wages with respect to the unemployment rate is

$$\frac{\hat{W}_{LR}}{\hat{u}_{LR}^R} = \frac{\hat{\beta}_1^*}{1 - \hat{\beta}_2} = \frac{\dfrac{\nu_2 [e^{-1} e_W e_u - e_{Wu}] u^R}{e_{WW} e e_W^{-1} (1 - \nu_1 \omega)}}{1 - \dfrac{\nu_1 (1 - \omega)}{1 - \nu_1 \omega}} = \frac{\nu_2 [e^{-1} e_W e_u - e_{Wu}] u^R}{(1 - \nu_1) e_{WW} e e_W^{-1}} . \tag{15}$$ [18]

The analysis in this section does not explicitly consider technology shocks. However, equations (9) and (10) show that technology shocks and demand shocks have proportional effects on wages and unemployment, since the coefficient on technology is $(\gamma - 1)/\gamma$ times the coefficient on demand in both equations. Thus, modeling a technology shock would yield the same regression coefficients that were derived in this section.

In addition, the model assumes that wages are set unilaterally by firms. If it is instead assumed that wages are determined from bargaining between firms and their employees, the equilibrium wage would depend on the assumptions of the bargaining model. Suppose that the wage negotiated between firms and workers is chosen to maximize the function, $V = U^{\lambda}\Pi^{1-\lambda}$, where U is the workers' objective function, Π is the firm's profits, and λ represents the union's relative bargaining strength. If the workers' objective function is $U = W(1-u) - \overline{U} = W(L/N) - \overline{U}$ (where $W(1\text{-}u)$ is total income and $\overline{U}$ is the reservation utility level), then it can be demonstrated that maximizing V yields equation (4). Thus, if efficiency depends on wages and unemployment and if workers seek to maximize total income, a bargaining model and an efficiency wage model yield the same solution for the wage and for the relationship between wages and unemployment. The reason why both models yield the same solution is that labor income and profits are constant proportions of total revenue in the model developed here, so firms and workers both have the incentive to choose the wage that maximizes total revenue.[19]

It could also be assumed that workers bargain over the wage instead of total income, so that their objective function is $U = W - \overline{U}$. If reservation utility is a constant fraction of the average wage, it can be demonstrated that the solution looks like equation (4), except that the right-hand side is a constant that is less than 1. In this case, linearizing the model around its steady state still yields a wage curve, although the coefficient on unemployment is lower than in the efficiency wage case. However, under reasonable conditions, the coefficient may be similar to the coefficient in a pure efficiency wage model.[20]

5. Numerical wage curve estimates

If numerical values are assigned to the model's parameters, the magnitudes of the long-run wage curve elasticity (equation 15), the short-run wage curve elasticity (equation 14c), and the coefficient on lagged wages (equation 14b) can be determined. Baseline values for these parameters are chosen, and the short- and long-run wage curve elasticities and the coefficient on lagged wages are calculated. Then the robustness of the results is examined by varying parameters from their baseline values.

For the baseline parameters, ν_1 (the weight workers place on local wages in comparing their own wages to a benchmark), ν_2 (the weight they place on local unemployment), and ω (the degree to which expectations are unbiased) are assumed to equal 0.5. In addition, u^R (the regional unemployment rate) and *e* (average efficiency) are set at 0.06 and 0.8, respectively. It is assumed that e_W equals *e*, since (from equation 4) $e^{-1}e_W = \Omega_t / W_t$, and the ratio between Ω_t and W_t should, on average, equal 1. A value for e_u is chosen so that the elasticity of efficiency with respect to the unemployment rate equals 0.05, based on Wadhwani and Wall's (1991) and Weisskopf's (1987) estimates of the effect of unemployment on productivity.[21]

There is little empirical evidence concerning the magnitudes of e_{WW} and e_{Wu}. To obtain values for these parameters, specific assumptions are made about the form of the efficiency function. Two specifications for the efficiency function are considered. The first specification (referred to as the naïve efficiency function) is

$$e = \ln\left[a_1 + a_2 \frac{W_t}{\Omega_t} + a_3 u_t^R\right], \qquad \text{with } a_2>0 \text{ and } a_3>0.$$

The second specification (referred to as the micro-based efficiency function) is derived in Campbell (2006), which develops a model in which a worker's choice of effort is determined in a utility-maximizing framework, based on the shirking and fair wage versions of efficiency wage theory. Both efficiency specifications have three free parameters, and the assumptions concerning e, e_W, and e_u determine these parameters, allowing values for e_{WW} and e_{Wu} to be calculated.[22]

An advantage of the second specification is that it is derived in a rigorous framework from utility-maximizing behavior. On the other hand, the first specification is more general, whereas the second specification comes from a model that is based on two versions of efficiency wage theory and that ignores other reasons why productivity may depend on wages (e.g., turnover and adverse selection). Using two specifications that are obtained in very different ways provides a check on the robustness of the results.

Table 1 reports $\hat{\beta}_1^*$ (the coefficient on unemployment in the log-log specification), $\hat{\beta}_2$ (the coefficient on lagged wages), and the long-run wage curve elasticity. In the baseline specification, the long-run elasticity is -0.1125 with the naïve efficiency function and -0.0748 with the micro-based efficiency function. Empirical values for this elasticity have been estimated with data from many countries by Blanchflower and Oswald (1994) and others. The vast majority of studies report long-run elasticities between -0.03 and -0.20. Nijkamp and Poot (2005) conduct a meta-analysis on a sample of 208 wage curve elasticities and find that the mean elasticity is about -0.12. However, when they control for publication bias, they estimate that the average wage curve elasticity is about -0.07. Thus, with both efficiency functions, the elasticities calculated with the baseline parameters are well within the range of values that have been estimated empirically.

Table 1 also reports the results when parameters are above and below their baseline values, and all but one long-run elasticity lies between -0.03 and -0.20. This table shows that changes in parameters other than ν_1 and ν_2 have relatively small effects on the wage curve elasticity. The fact that the wage curve elasticity is relatively invariant to changes in most of the parameters and to different specifications of the efficiency function may explain why researchers have found similar elasticities for many countries.

The two parameters that have a large effect on the wage curve elasticity are ν_1 and ν_2. As the ν's increase, the predicted wage curve elasticity rises substantially, consistent with the results of Longhi et al. (2006), who find higher wage curve elasticities in labor markets that are more isolated (i.e., ones with lower degrees of agglomeration/ accessibility). It is likely that ν_1 and ν_2 are higher in these areas, since workers in these regions should be less influenced by external wages and unemployment.

Table 1 also reports the coefficient on lagged wages ($\hat{\beta}_2$). None of these values is close to 1, in agreement with the wage curve literature. However, most of the predicted coefficients are smaller than typical empirical estimates. For example, Montuenga-Gómez and Ramos-Parreño (2005) report a total of 21 coefficients on lagged wages obtained from 16 wage curve studies. The average value of these coefficients is 0.44, and the interquartile range is 0.28 to 0.65. While most of the predicted coefficients in Table 1 are below the average value, the coefficients are close to 0.44 in the second row, in which expectations are assumed to be mostly adaptive (i.e., ω=0.25), and in the last row, in which ν_1=0.6 and ν_2=0.4. These values of ν_1 and ν_2 imply that workers place a slightly higher weight on regional wages than on national wages but place a slightly higher weight on national unemployment than on regional unemployment. It seems plausible that ν_1>0.5 and ν_2<0.5, since workers may have greater knowledge of wages in their region than of wages in the rest of the economy, but may have greater knowledge of national unemployment than of local unemployment, because national figures are highly publicized.

6. A model of the aggregate economy

This section examines the behavior of aggregate wages and unemployment. At the aggregate level, both ν_1 and ν_2 equal 1, and Ω^R and u^R can be replaced with Ω and u. When the aggregate economy experiences a one-time permanent demand shock, the paths of wages and unemployment are

$$\hat{W}_t = (1-\mu^t)S, \quad \text{and} \tag{16a}$$

$$du_t = z_2 \mu^{t-1} S, \qquad \text{where} \qquad z_2 = \frac{s_L(1-\omega)[\alpha\gamma + \phi(\gamma-1)]}{[1+\alpha(1-\omega)]\eta} < 0.^{23} \tag{16b}$$

This demand shock eventually raises wages by the same percentage amount, since $\hat{W}_t = S$ as t approaches infinity. However, wages adjust gradually to their new equilibrium, so unemployment initially rises or falls from its original level. Over time, unemployment returns to its original level, implying that the economy has a natural rate of unemployment. (The economy also returns to its natural rate after a technology shock.) At the aggregate level, there is no equilibrium relationship between wages and unemployment since demand shocks have permanent effects on wages but have no long-run effects on unemployment.

At the aggregate level, the regression $\hat{W}_t = \hat{\beta}_1 du_t + \hat{\beta}_2 \hat{W}_{t-1} + \varepsilon_t$ yields the coefficients

$$\hat{\beta}_1 = \frac{e^{-1} e_W e_u - e_{Wu}}{e_{WW} e e_W^{-1} (1-\omega)} \quad \text{and} \tag{17a}$$

$$\hat{\beta}_2 = 1. \tag{17b}$$

Since $\hat{\beta}_2 = 1$, the unemployment rate is related to the rate of change in wages, so the aggregate economy is characterized by a Phillips curve.[24] In this Phillips curve relationship, unemployment and wages are endogenously determined by the profit-maximizing behavior of firms during the economy's transition between its initial equilibrium and its new equilibrium. The Phillips curve is a disequilibrium relationship, since it is determined from wages and unemployment in the transition between equilibia.

The slope of the Phillips Curve is given by equation (17a). In the limiting case in which ω =1 (i.e., expectations are unbiased), the Phillips curve is vertical, as predicted by proponents of new classical macroeconomics. With the baseline parameters from Section 5, $\hat{\beta}_1$ equals -3.75 with the naïve efficiency function and -2.49 with the micro-based efficiency function. However, when Phillips curves are estimated with annual data, the estimated coefficients tend to be smaller than these the predicted values. (It is more reasonable to compare the predicted coefficients with estimates from annual regressions than from quarterly regressions, since the model assumes that wages are set each period and most people's wages are set each year.) For example, with annual data, Blanchard and Katz (1997) estimate coefficients on the unemployment rate that lie between -0.95 and -1.02.

While the predicted values of $\hat{\beta}_1$ are higher than values that have been estimated empirically, there are two ways in which the present model can be reconciled with these empirical results. First, a lower value of ω would result in a lower predicted coefficient.

Second, in the model developed in this study, imperfect information is the only reason for the slow adjustment of wages in response to shocks. In reality, however, there may be other impediments to wage adjustment. One possibility is that workers' effort may depend on wage changes as well as on wage levels. Evidence that effort depends on wage changes is discussed in Kahneman et al. (1986), Campbell and Kamlani (1997), Bewley (1994), and Clark (1999).[25] Also, Akerlof (2007) considers workers' concerns about wage norms (which may depend on past wages) to be one of the "missing motivations" in macroeconomics.

Modified versions of the model were derived in which efficiency depends on wage changes as well as on wage levels (with the elasticity of efficiency with respect to wage changes set equal to 1). In one version efficiency depends on absolute wage changes and in the other it depends on relative wage changes. When ω is assumed to equal 0.25 (instead of 0.5), the value of $\hat{\beta}_1$ in the modified model lies between -0.713 and -1.22, a range consistent with empirical estimates.[26]

7. Simulations with a multiregional economy

Section 4 derives regression coefficients for the relationship between wages and unemployment in a single region, in isolation from other regional economies. In Section 6 regression coefficients are derived for the aggregate economy, treating the aggregate economy as a single entity rather than as the average of regional economies. This section demonstrates that similar results are obtained in an economy consisting of different regions, in which efficiency depends on both regional and national labor market conditions. The behavior of an economy consisting of 10 regions is simulated over 20 time periods, under the assumption that there are stochastic aggregate and regional specific demand shocks in each period.[27] The parameters are the same as the baseline parameters (with the micro-based efficiency function) in Section 5, and a total of 50 simulations were performed.

With each simulation, regional wages and unemployment in each time period are treated as data in a pooled cross-section time-series regression. Regressions are run both with and without lagged regional wages, and two specifications for the unemployment rate are considered. The first specification is du_t^R / u^* (where u* is the natural rate of unemployment), which is analogous to log-level estimation since it treats a given change in unemployment as having the same effect on $\hat{W}_t$ at any unemployment rate. The second specification for unemployment is $\ln[u^* + du_t^R]$. With this specification, a given change in unemployment has a larger effect on $\hat{W}_t$ as unemployment falls, and it is analogous to log-log estimation. In addition, these regressions also include time dummy variables.

Table 2a reports the results of these regressions. For each variable, the top row is the average value across all 50 simulations, and the bottom row (in parentheses) gives the lowest and highest values. Several results are worth noting. First, in column 1 (which includes lagged wages and the first specification for unemployment), the coefficients on unemployment and lagged wages are always the same as the baseline values in Table 1, in which a single labor market is considered in isolation. These results suggest that considering a single region by itself does not give misleading results.

Second, the R^2's are always higher with the log-level specification than with the log-log specification. However, as previously discussed, a log-log specification may provide a better fit if the ν's depend negatively on the difference between regional and aggregate unemployment. If the ν's are functions of u^R-u^N, the relationship between regional wages and unemployment will be nonlinear, and a log-log specification may approximately capture this nonlinearity. In addition, the coefficient on lagged wages may be different than the value predicted by (6a) and (6b) if the ν's are functions of u^R-u^N.

To examine the implications of the ν's depending on unemployment differentials, simulations were run under the assumption that $\nu_{1,i,t} = \nu_{2,i,t} = 0.5 - 2(du_{i,t}^R - du_t^N)$, where $\nu_{1,i,t}$ and $\nu_{2,i,t}$ are the values of ν_1 and ν_2 in region i at time t.[28] Table 2b reports wage equations estimated with these simulated data. In this table a log-log specification outperforms a log-level specification, providing a potential explanation for why a log-log specification generally fits the data better than a log-level specification in estimating wage curves. In addition, with the log-log specification the average coefficient on lagged wages is closer to 0.333 (the value predicted by (6a) and (6b)) than with the log-level specification, and it is only 5% different from the predicted value.[29]

The regional data are then averaged to form aggregate time-series data. With these data, wages are regressed on unemployment and lagged wages, and the results are reported in Table 2c. The coefficients on the unemployment rate and lagged wages are identical to those calculated in Section 6. Thus, the same coefficients are obtained if we view the aggregate economy as a single entity or as an average of regional economies.

These simulations show that regional data on wages and unemployment produce a wage curve when pooled wage equations are estimated and yield a Phillips curve when regional data are averaged to form aggregate data. Thus, these simulations can explain why different conclusions about the relationship between wages and unemployment have been reached by researchers who have estimated wage equations with individual or regional data and those who have estimated wage equations with aggregate data.

These simulations assume that labor supply in each region is fixed. However, as discussed in Layard, Nickell, and Jackman (1991), workers can migrate between regions in response to differences in labor market conditions. To examine the effect of migration in the model, simulations were run in which migration into a region depends positively on the difference between regional and national wages and negatively on the difference between regional and national unemployment. The coefficients in the migration equation were determined from the migration equation estimated by Layard et al. (1991, p. 316) for the U.S., and 50 simulations were performed.

Regressions of the same form as those in Table 2a were estimated with the simulated data, and the results are reported in Table 2d. The coefficients in Tables 2a and 2d are identical in the first column and are not very different in the other three columns. Thus, similar wage curves are obtained from simulations assuming fixed regional labor supply and simulations incorporating migration. One difference, though, is that allowing migration greatly reduces the variance of unemployment across regions and time.

8. Conclusion

This study develops an efficiency wage model that predicts the coefficients on unemployment and lagged wages in a wage equation and that predicts the paths followed by wages and unemployment in response to demand shocks. The wage equation looks like a wage curve when regional economies are modeled and looks like a Phillips curve at the national level.

The model predicts different behavior at the regional and aggregate levels because of the assumptions about the determinants of workers' efficiency. In modeling a regional economy, it is assumed that efficiency depends on both regional and national economic conditions. As a result, the coefficient on lagged wages is less than 1, and there is an equilibrium relationship between regional wages and unemployment. However, in modeling the aggregate economy, there is no distinction between the regional and national economies, which results in lagged wages having a coefficient of 1 and the economy returning to a natural rate of unemployment. Because unemployment eventually returns to its natural rate, there is no long-term relationship between wages and unemployment. Thus, the Phillips curve is a disequilibrium relationship that is determined from the paths of wages and unemployment in the transition between equilibria.

When reasonable parameter values are chosen, the calculated wage curve elasticities are generally close to empirically estimated values. In addition, if expectations are assumed to be mostly adaptive and if the model is modified to allow efficiency to depend on both wage levels and wage changes, the predicted slope of the Phillips curve is close to values that have been estimated empirically.

This study also considers simulations of a multiregional economy in which there are aggregate and region-specific demand shocks in each period. Data on regional wages and unemployment yield a wage curve when pooled regressions are estimated, and the coefficients in this wage curve are the same as the coefficients obtained when a single regional economy is considered in isolation. When the regional data are averaged to form aggregate data, the relationship between wages and unemployment at the national level is a Phillips curve. Thus, it is demonstrated that there is no contradiction between studies that find evidence for a wage curve with regional data and those finding evidence for a Phillips curve with aggregate data.

Appendix A

When equation (2) is totally differentiated and divided by the original equation, the solution for $\hat{L}_t$ is

$$\hat{L}_t = \frac{\gamma\hat{W}_t - \gamma\hat{\theta}_t - (\gamma-1)\hat{A}_t - \phi(\gamma-1)e^{-1}[e_W \frac{W_t}{\Omega_t}\hat{W}_t - e_W \frac{W_t}{\Omega_t}\hat{\Omega}_t + e_u du_t]}{\phi(\gamma-1)-\gamma}. \qquad (A1)$$

By making the substitutions $\hat{\Omega}_t = \nu_1\hat{\Omega}_t^R + (1-\nu_1)\hat{\Omega}_t^N$, $du_t = \nu_2 du_t^R + (1-\nu_2)du_t^N$, $du_t^R = -s_L\hat{L}_t$, and $W_t/\Omega_t = ee_w^{-1}$, the solution for $\hat{L}_t$ becomes

$$\begin{aligned}\hat{L}_t = \frac{1}{\eta}\Big[&[\gamma - \phi(\gamma-1)]\hat{W}_t + \nu_1\phi(\gamma-1)\hat{\Omega}_t^R + \phi(\gamma-1)(1-\nu_1)\hat{\Omega}_t^N - \gamma\hat{\theta}_t \\ &-(\gamma-1)\hat{A}_t - \phi(\gamma-1)(1-\nu_2)e^{-1}e_u du_t^N\Big],\end{aligned} \qquad (A2)$$

where

$$\eta = \phi\gamma - \phi - \gamma - \phi(\gamma-1)e^{-1}s_L\nu_2 e_u .$$

If (A2) and the relationship $\hat{\Omega}_t^R = \omega\hat{W}_t + (1-\omega)\hat{W}_{t-1}$ are substituted into the equation $du_t^R = -s_L\hat{L}_t$, the following equation for the regional unemployment rate is obtained:

$$\begin{aligned}du_t^R = -\frac{s_L}{\eta}\Big[&[\gamma - \phi(\gamma-1)(1-\nu_1\omega)]\hat{W}_t + \nu_1\phi(\gamma-1)(1-\omega)\hat{W}_{t-1} \\ &+\phi(\gamma-1)(1-\nu_1)\hat{\Omega}_t^N - \gamma\hat{\theta}_t - (\gamma-1)\hat{A}_t - \phi(\gamma-1)(1-\nu_2)e^{-1}e_u du_t^N\Big].\end{aligned} \qquad (A3)$$

Substituting (A3) into equation (6a) yields

$$\left[1+\frac{s_L\nu_2[e^{-1}e_W e_u - e_{Wu}][\gamma-\phi(\gamma-1)(1-\nu_1\omega)]}{e_{WW}ee_W^{-1}(1-\nu_1\omega)\eta}\right]\hat{W}_t$$

$$=\left[\frac{\nu_1(1-\omega)}{1-\nu_1\omega}-\frac{s_L\nu_2[e^{-1}e_W e_u - e_{Wu}]\nu_1\phi(\gamma-1)(1-\omega)}{e_{WW}ee_W^{-1}(1-\nu_1\omega)\eta}\right]\hat{W}_{t-1}$$

$$+\left[\frac{1-\nu_1}{1-\nu_1\omega}-\frac{s_L\nu_2[e^{-1}e_W e_u - e_{Wu}]\phi(\gamma-1)(1-\nu_1)}{e_{WW}ee_W^{-1}(1-\nu_1\omega)\eta}\right]\hat{\Omega}_t^N$$

$$+\frac{s_L\nu_2\gamma[e^{-1}e_W e_u - e_{Wu}]}{e_{WW}ee_W^{-1}(1-\nu_1\omega)\eta}\hat{\theta}_t+\frac{s_L\nu_2(\gamma-1)[e^{-1}e_W e_u - e_{Wu}]}{e_{WW}ee_W^{-1}(1-\nu_1\omega)\eta}\hat{A}_t$$

$$+\frac{e^{-1}e_W e_u - e_{Wu}}{e_{WW}ee_W^{-1}(1-\nu_1\omega)}\left[1-\nu_2+\frac{s_L\nu_2\phi(\gamma-1)(1-\nu_2)e^{-1}e_u}{\eta}\right]du_t^N .$$

If this equation is multiplied by the reciprocal of the coefficient on $\hat{\theta}_t$, it can be expressed as

$$\left[\frac{e_{WW}ee_W^{-1}(1-\nu_1\omega)\eta}{s_L\nu_2\gamma\left(e^{-1}e_W e_u - e_{Wu}\right)}-\frac{\phi(\gamma-1)(1-\nu_1\omega)}{\gamma}+1\right]\hat{W}_t$$
$$=\nu_1(1-\omega)\left[\frac{e_{WW}ee_W^{-1}\eta}{s_L\nu_2\gamma\left(e^{-1}e_W e_u - e_{Wu}\right)}-\frac{\phi(\gamma-1)}{\gamma}\right]\hat{W}_{t-1}$$
$$+(1-\nu_1)\left[\frac{e_{WW}ee_W^{-1}\eta}{s_L\nu_2\gamma\left(e^{-1}e_W e_u - e_{Wu}\right)}-\frac{\phi(\gamma-1)}{\gamma}\right]\hat{\Omega}_t^N \tag{A4}$$
$$+\hat{\theta}_t+\frac{\gamma-1}{\gamma}\hat{A}_t+(1-\nu_2)\frac{\phi\gamma-\phi-\gamma}{s_L\nu_2\gamma}du_t^N .$$

Defining α as

$$\alpha=\frac{e_{WW}ee_W^{-1}\eta}{s_L\nu_2\gamma\left(e^{-1}e_W e_u - e_{Wu}\right)}-\frac{\phi(\gamma-1)}{\gamma},$$

allows (A4) to be written as

$$[1+\alpha(1-\nu_1\omega)]\hat{W}_t - \nu_1\alpha(1-\omega)\hat{W}_{t-1} = \hat{\theta}_t + \frac{\gamma-1}{\gamma}\hat{A}_t + \alpha(1-\nu_1)\hat{\Omega}_t^N + (1-\nu_2)\frac{\phi\gamma-\phi-\gamma}{s_L\nu_2\gamma}du_t^N.$$

Dividing by the coefficient on $\hat{W}_t$ produces the equation:

$$\hat{W}_t - \mu\hat{W}_{t-1} = \frac{1}{1+\alpha(1-\nu_1\omega)}\hat{\theta}_t + \frac{\gamma-1}{\gamma[1+\alpha(1-\nu_1\omega)]}\hat{A}_t + \frac{\alpha(1-\nu_1)}{1+\alpha(1-\nu_1\omega)}\hat{\Omega}_t^N + (1-\nu_2)\frac{\phi\gamma-\phi-\gamma}{s_L\nu_2\gamma[1+\alpha(1-\nu_1\omega)]}du_t^N, \tag{A5}$$

where

$$\mu = \frac{\nu_1\alpha(1-\omega)}{1+\alpha(1-\nu_1\omega)}.$$

Equation (A5) is a first-order difference equation, and it can be rewritten as

$$\hat{W}_t = \frac{1}{1-\mu L}\left[\frac{1}{1+\alpha(1-\nu_1\omega)}\hat{\theta}_t + \frac{\gamma-1}{\gamma[1+\alpha(1-\nu_1\omega)]}\hat{A}_t + \frac{\alpha(1-\nu_1)}{1+\alpha(1-\nu_1\omega)}\hat{\Omega}_t^N + (1-\nu_2)\frac{\phi\gamma-\phi-\gamma}{s_L\nu_2\gamma[1+\alpha(1-\nu_1\omega)]}du_t^N\right]. \tag{A6}$$

Using the relationship, $\frac{x_t}{1-\mu L} = \sum_{j=0}^{\infty}\mu^j x_{t-j}$, the following equation for $\hat{W}_t$ is obtained:

$$\hat{W}_t = \frac{1}{1+\alpha(1-\nu_1\omega)}\sum_{j=0}^{\infty}\mu^j\hat{\theta}_{t-j} + \frac{\gamma-1}{\gamma[1+\alpha(1-\nu_1\omega)]}\sum_{j=0}^{\infty}\mu^j\hat{A}_{t-j} + \frac{\alpha(1-\nu_1)}{1+\alpha(1-\nu_1\omega)}\sum_{j=0}^{\infty}\mu^j\hat{\Omega}_{t-j}^N + (1-\nu_2)\frac{\phi\gamma-\phi-\gamma}{s_L\nu_2\gamma[1+\alpha(1-\nu_1\omega)]}\sum_{j=0}^{\infty}\mu^j du_{t-j}^N. \tag{A7}$$

Appendix B

This appendix derives expressions for wages and unemployment over time in response to a series of stochastic demand shocks (with technology, wages in other labor markets, and unemployment in other labor markets held constant). Suppose that $\hat{\theta}_t = 0$ for $t \le 0$, and that $\theta_t = \theta_{t-1} + \varepsilon_t$ for $t \ge 1$. Then, $\hat{\theta}_t = \sum_{i=1}^{t} \varepsilon_i$ for $t \ge 1$. In this case, equation (9) becomes

$$\hat{W}_t = \frac{1}{1+\alpha(1-\nu_1\omega)} \sum_{j=0}^{t-1} \mu^j \hat{\theta}_{t-j}$$

$$= \frac{1}{1+\alpha(1-\nu_1\omega)} \left[\sum_{i=1}^{t} \varepsilon_i + \mu \sum_{i=1}^{t-1} \varepsilon_i + \mu^2 \sum_{i=1}^{t-2} \varepsilon_i + \mu^3 \sum_{i=1}^{t-3} \varepsilon_i + \cdots + \mu^{t-1} \varepsilon_1 \right]$$

$$= \frac{1}{1+\alpha(1-\nu_1\omega)} \left[\varepsilon_t \frac{1-\mu}{1-\mu} + \varepsilon_{t-1} \frac{1-\mu^2}{1-\mu} + \varepsilon_{t-2} \frac{1-\mu^3}{1-\mu} + \cdots + \varepsilon_1 \frac{1-\mu^t}{1-\mu} \right]$$

$$= \frac{1}{(1-\mu)[1+\alpha(1-\nu_1\omega)]} \sum_{i=1}^{t} \varepsilon_i (1-\mu^{t-i+1})$$

$$= \frac{1}{\left(1 - \frac{\nu_1 \alpha(1-\omega)}{1+\alpha(1-\nu_1\omega)}\right)[1+\alpha(1-\nu_1\omega)]} \sum_{i=1}^{t} \varepsilon_i (1-\mu^{t-i+1})$$

$$\hat{W}_t = \frac{1}{1+\alpha(1-\nu_1)} \sum_{i=1}^{t} \varepsilon_i (1-\mu^{t-i+1}) .$$

If we let $\xi = \frac{1}{1+\alpha(1-\nu_1)}$, then equation (10) can be expressed as

$$du_t^R = -\frac{s_L}{\eta}\left[[\gamma - \phi(\gamma-1)(1-\nu_1\omega)]\xi\sum_{i=1}^{t}\varepsilon_i(1-\mu^{t-i+1}) \right.$$

$$\left. + \phi(\gamma-1)(1-\omega)\nu_1\xi\sum_{i=1}^{t-1}\varepsilon_i(1-\mu^{t-i}) - \gamma\sum_{i=1}^{t}\varepsilon_i \right]$$

$$= -\frac{s_L}{\eta}\left[\gamma\xi\sum_{i=1}^{t}\varepsilon_i - \gamma\xi\sum_{i=1}^{t}\varepsilon_i\mu^{t-i+1} - \phi(\gamma-1)(1-\nu_1\omega)\xi\sum_{i=1}^{t}\varepsilon_i(1-\mu^{t-i+1}) \right.$$

$$\left. + \phi(\gamma-1)\xi[(1-\nu_1\omega)-(1-\nu_1)]\sum_{i=1}^{t-1}\varepsilon_i(1-\mu^{t-i}) - \gamma\sum_{i=1}^{t}\varepsilon_i \right]$$

$$= -\frac{s_L}{\eta}\left[-\gamma\xi\sum_{i=1}^{t}\varepsilon_i\mu^{t-i+1} - \phi(\gamma-1)(1-\nu_1\omega)\xi\left(\sum_{i=1}^{t}\varepsilon_i(1-\mu^{t-i+1}) - \sum_{i=1}^{t-1}\varepsilon_i(1-\mu^{t-i}) \right) \right.$$

$$\left. - \phi(\gamma-1)\xi(1-\nu_1)\sum_{i=1}^{t-1}\varepsilon_i(1-\mu^{t-i}) - \gamma(1-\xi)\sum_{i=1}^{t}\varepsilon_i \right]$$

$$= -\frac{s_L}{\eta}\left[-\gamma\xi\mu\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} - \phi(\gamma-1)(1-\nu_1\omega)\xi(1-\mu)\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} - \phi(\gamma-1)\xi(1-\nu_1)\sum_{i=1}^{t-1}\varepsilon_i \right.$$

$$\left. + \phi(\gamma-1)\xi(1-\nu_1)\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} - \phi(\gamma-1)\xi(1-\nu_1)\varepsilon_t - \gamma(1-\xi)\sum_{i=1}^{t}\varepsilon_i \right]$$

$$= -\frac{s_L}{\eta}\left[[-\phi(\gamma-1)(1-\nu_1)\xi - \gamma(1-\xi)]\sum_{i=1}^{t}\varepsilon_i \right.$$

$$\left. + \xi[-\gamma\mu + \phi(\gamma-1)(\mu + \nu_1\omega - \mu\nu_1\omega - \nu_1)]\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} \right]$$

$$du_t^R = \frac{s_L}{\eta}\left[\frac{(1-\nu_1)[\alpha\gamma + \phi(\gamma-1)]}{1+\alpha(1-\nu_1)}\sum_{i=1}^{t}\varepsilon_i + \frac{(1-\omega)\nu_1[\alpha\gamma+\phi(\gamma-1)]}{[1+\alpha(1-\nu_1)][1+\alpha(1-\nu_1\omega)]}\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} \right].$$

Thus, du_t^R can be written as

$$du_t^R = z_1\sum_{i=1}^{t}\varepsilon_i + z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-i},$$

where

$$z_1 = \frac{s_L(1-\nu_1)[\alpha\gamma + \phi(\gamma-1)]}{[1+\alpha(1-\nu_1)]\eta}, \quad \text{and}$$

$$z_2 = \frac{s_L(1-\omega)\nu_1[\alpha\gamma + \phi(\gamma-1)]}{[1+\alpha(1-\nu_1)][1+\alpha(1-\nu_1\omega)]\eta}.$$

It can be shown that z_1 and z_2 are both negative. The first term in α is unambiguously positive, since $e_{WW} < 0$, $e_{Wu} < 0$, $e_u > 0$, and $\eta < 0$. Thus,

$$\alpha > -\frac{\phi(\gamma-1)}{\gamma}.$$

The fact that $\alpha > -[\phi(\gamma-1)/\gamma] > -1$ means that $[\alpha\gamma + \phi(\gamma-1)] > 0$, $[1+\alpha(1-\nu_1\omega)] > 0$, and $[1+\alpha(1-\nu_1)] > 0$. As a result, z_1 and z_2 are both unambiguously negative.

Appendix C

The values of $\hat{\beta}_1$ and $\hat{\beta}_2$ can be calculated by using the relationship $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$, where **y** is a vector of wages from period 1 through period *T* and **X** is a matrix whose first column is the unemployment rate from periods 1 through *T* and whose second column is wages from periods 0 through *T* -1. Using this equation, the values of $\hat{\beta}_1$ and $\hat{\beta}_2$ can be demonstrated to equal

$$\hat{\boldsymbol{\beta}} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} = \begin{bmatrix} \dfrac{1-\mu}{(z_1+z_2)[1+\alpha(1-v_1)]} \\ \dfrac{\mu z_1 + z_2}{z_1+z_2} \end{bmatrix}. \tag{C1}$$

However, the derivation of $\hat{\beta}_1$ and $\hat{\beta}_2$ from the equation $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ is quite tedious and is not reported here, since there is a simpler way of showing that these are the correct values of the coefficients. For both a one-time permanent demand shock and a series of stochastic demand shocks, the regression equations have a perfect fit.[30] Since the equation $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ is derived by minimizing $(\mathbf{y}-\mathbf{X}\hat{\boldsymbol{\beta}})'(\mathbf{y}-\mathbf{X}\hat{\boldsymbol{\beta}})$, the values of $\hat{\beta}_1$ and $\hat{\beta}_2$ in (C1) can be demonstrated to be correct by showing that $\mathbf{y} = \mathbf{X}\hat{\boldsymbol{\beta}}$ (i.e., that $\hat{W}_t = \hat{\beta}_1 du_t^R + \hat{\beta}_2 \hat{W}_{t-1}$ for all values of *t*). For a series of stochastic demand shocks,

$$\hat{\beta}_1 du_t^R + \hat{\beta}_2 \hat{W}_{t-1} = \frac{(1-\mu)\left(z_1 \sum_{i=1}^{t} \varepsilon_i + z_2 \sum_{i=1}^{t} \varepsilon_i \mu^{t-i}\right)}{(z_1+z_2)[1+\alpha(1-v_1)]} + \frac{\mu z_1 + z_2}{z_1+z_2} \frac{\sum_{i=1}^{t-1} \varepsilon_i (1-\mu^{t-i})}{1+\alpha(1-v_1)}$$

$$= \frac{\begin{array}{l} z_1\sum_{i=1}^{t}\varepsilon_i - \mu z_1\sum_{i=1}^{t}\varepsilon_i + z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} - \mu z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} \\ + \mu z_1\sum_{i=1}^{t-1}\varepsilon_i - \mu z_1\sum_{i=1}^{t-1}\varepsilon_i\mu^{t-i} + z_2\sum_{i=1}^{t-1}\varepsilon_i - z_2\sum_{i=1}^{t-1}\varepsilon_i\mu^{t-i} \end{array}}{(z_1+z_2)[1+\alpha(1-\nu_1)]}$$

$$= \frac{\begin{array}{l} z_1\sum_{i=1}^{t}\varepsilon_i - \mu z_1\sum_{i=1}^{t}\varepsilon_i + z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} - \mu z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} + \mu z_1\sum_{i=1}^{t}\varepsilon_i - \mu z_1\varepsilon_t \\ - \mu z_1\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} + \mu z_1\varepsilon_t + z_2\sum_{i=1}^{t}\varepsilon_i - z_2\varepsilon_t - z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} + z_2\varepsilon_t \end{array}}{(z_1+z_2)[1+\alpha(1-\nu_1)]}$$

$$= \frac{z_1\sum_{i=1}^{t}\varepsilon_i - \mu z_2\sum_{i=1}^{t}\varepsilon_i\mu^{t-1} - \mu z_1\sum_{i=1}^{t}\varepsilon_i\mu^{t-i} + z_2\sum_{i=1}^{t}\varepsilon_i}{(z_1+z_2)[1+\alpha(1-\nu_1)]}$$

$$= \frac{\sum_{i=1}^{t}\varepsilon_i - \mu\sum_{i=1}^{t}\varepsilon_i\mu^{t-i}}{1+\alpha(1-\nu_1)}$$

$$= \frac{\sum_{i=1}^{t}\varepsilon_i(1-\mu^{t-i+1})}{1+\alpha(1-\nu_1)}$$

$$\hat{\beta}_1 du_t^R + \hat{\beta}_2\hat{W}_{t-1} = \hat{W}_t .$$

A one-time permanent demand shock is a special case (with $\varepsilon_1 = S$ and $\varepsilon_t = 0$ for $t \geq 2$) of the above derivation, so the predicted coefficients would be the same.

The expressions for $\hat{\beta}_1$ and $\hat{\beta}_2$ can now be simplified. The value of $\hat{\beta}_1$ is

$$\hat{\beta}_1 = \frac{1-\mu}{(z_1+z_2)[1+\alpha(1-\nu_1)]}.$$

Substituting expressions for μ, z_1, and z_2 into the above equation yields

$$\hat{\beta}_1 = \frac{\dfrac{1}{1+\alpha(1-\nu_1)}\left(1-\dfrac{\nu_1\alpha(1-\omega)}{1+\alpha(1-\nu_1\omega)}\right)}{\dfrac{s_L(1-\nu_1)[\alpha\gamma+\phi(\gamma-1)]}{[1+\alpha(1-\nu_1)]\eta}+\dfrac{s_L(1-\omega)\nu_1[\alpha\gamma+\phi(\gamma-1)]}{[1+\alpha(1-\nu_1)][1+\alpha(1-\nu_1\omega)]\eta}}$$

$$= \frac{\eta[1+\alpha(1-\nu_1)]}{s_L(1-\nu_1)[\alpha\gamma+\phi(\gamma-1)][1+\alpha(1-\nu_1\omega)]+s_L(1-\omega)\nu_1[\alpha\gamma+\phi(\gamma-1)]}$$

$$\hat{\beta}_1 = \frac{\eta}{s_L[\alpha\gamma+\phi(\gamma-1)](1-\nu_1\omega)}.$$

Since α is defined as

$$\alpha = \frac{e_{WW}ee_W^{-1}\eta}{s_L\nu_2\gamma[e^{-1}e_We_u-e_{Wu}]}-\frac{\phi(\gamma-1)}{\gamma},$$

it follows that

$$\hat{\beta}_1 = \frac{\nu_2[e^{-1}e_We_u-e_{Wu}]}{e_{WW}ee_W^{-1}(1-\nu_1\omega)}<0.$$

The value of $\hat{\beta}_2$ is

$$\hat{\beta}_2 = \frac{\mu z_1+z_2}{z_1+z_2}$$

$$= \frac{\dfrac{\nu_1\alpha(1-\omega)}{1+\alpha(1-\nu_1\omega)}\dfrac{s_L(1-\nu_1)[\alpha\gamma+\phi(\gamma-1)]}{[1+\alpha(1-\nu_1)]\eta}+\dfrac{s_L(1-\omega)\nu_1[\alpha\gamma+\phi(\gamma-1)]}{[1+\alpha(1-\nu_1)][1+\alpha(1-\nu_1\omega)]\eta}}{\dfrac{s_L(1-\nu_1)[\alpha\gamma+\phi(\gamma-1)]}{[1+\alpha(1-\nu_1)]\eta}+\dfrac{s_L(1-\omega)\nu_1[\alpha\gamma+\phi(\gamma-1)]}{[1+\alpha(1-\nu_1)][1+\alpha(1-\nu_1\omega)]\eta}}$$

$$\hat{\beta}_2 = \frac{\nu_1(1-\omega)}{1-\nu_1\omega}<1.$$

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Footnotes

[1] The issue of whether the coefficient on lagged wages is less than one or equal to one is controversial. Blanchard and Katz (1997) estimate wage equations at the state level with several U.S. data sets, and they find a coefficient on lagged wages that is close to 1. In addition, Card and Hyslop's (1997) regressions with U.S. state data provide support for a Phillips curve relationship over a wage curve relationship. On the other hand, many studies (e.g., Blanchflower and Oswald (1994), Barth et al. (2002), and Blanchflower and Oswald (2005)) find coefficients on lagged wages that are significantly less than 1. As discussed in Section 5, Montuenga-Gómez and Ramos-Parreño (2005) report estimated coefficients on lagged wages obtained from 16 separate wage curve studies, and a total of 21 estimated coefficients are reported. The average of the reported coefficients is 0.44, and only three of the 21 coefficients are greater than 0.75. Thus, most of the empirical evidence suggests that the coefficient on lagged wages is significantly less than 1.

[2] Several studies use panel data to estimate wage curves. Bratsberg and Turunen (1996) and Turunen (1998) estimate wage curves for the United States with data from the National Longitudinal Survey of Youth, and Montuenga et al. (2003) use the European Community Household Panel data to estimate wage curves for five European countries.

[3] Technology shocks are not explicitly analyzed. However, as discussed in Section 4, the model developed in this study predicts that technology shocks and demand shocks will have proportionate effects on wages and unemployment, so the coefficients in a wage equation would be the same for both types of shocks.

[4] Two studies that consider both the wage curve and the Phillips curve are Roberts (1997b) and Whelan (2000). Roberts develops a staggered-contract model of wage setting for individual workers in which a worker's wage depends on the national price level, expectations of next period's national price level, and the log of the regional (or industry) unemployment rate. Under the assumption that prices are a constant markup over labor costs, he demonstrates that there is a Phillips curve (for price inflation) at the national level. In Whelan (2000), it is demonstrated that a Phillips curve at the aggregate level is consistent with any degree of wage autocorrelation at the microeconomic level. However, this study does not explain the factors that determine the degree of autocorrelation (ρ) and does not provide an explanation for why ρ would be less than 1 at the regional level.

[5] It should be noted that a pure Phillips curve relationship is not found in every country. As discussed in Montuenga-Gómez and Ramos-Parreño (2005, p. 757), evidence suggests that the United States is characterized by a pure Phillips curve, while most European countries are "characterized by a modified version of the Phillips curve with error correction but high autocorrelation."

[6] One difference between the present study and Galí and Gertler (1999) is that the present study assumes partly backward-looking expectations, while expectations in Galí and Gertler are mostly forward looking. However, Galí and Gertler consider the expectations of firms and the present study considers the expectations of workers, and it is likely that firms' expectations are more sophisticated than workers' expectations.

[7] The rationale for assuming that $e_{Wu} < 0$ is that de/dW is likely to fall as u rises. For example, when the unemployment rate is 6%, a firm that increases wages by 10% is likely to experience a significant fall in quits and a significant rise in effort. On the other hand, at an unemployment rate of 15%, quits are probably already low and effort is probably already high, so a firm raising wages by 10% would probably not see large additional changes in quits and effort. Thus, de/dW is probably smaller at a 15% unemployment rate than at a 6% unemployment rate. In addition, Campbell (2006) develops a model of workers' effort from utility-maximizing behavior and demonstrates that, given the model's assumptions, e_{Wu} is unambiguously negative.

[8] The reason for using geometric weights in the specification for Ω and arithmetic weights in the specification for u is that Ω is later expressed in terms of percentage deviations from its initial equilibrium value, while u is expressed in terms of absolute deviations from its initial equilibrium value. While it is probably more natural to use arithmetic weights rather than geometric weights, using arithmetic weights for Ω would not greatly affect the results of the study. First, if Ω_t^R and Ω_t^N are not too different, the arithmetic and geometric means are almost the same. Second, expressing Ω as a percentage deviation from its initial level yields $\hat{\Omega}_t = \nu_1 \Omega_t^R + (1-\nu_1)\Omega_t^N$ with geometric weights, and yields $\hat{\Omega}_t = s_\Omega \nu_1 \Omega_t^R + (1 - s_\Omega \nu_1)\Omega_t^N$ with arithmetic weights (where s_Ω equals the steady-state value of $\Omega^R/[\nu_1\Omega^R + (1-\nu_1)\Omega^N]$). Since s_Ω is likely to be close to 1, the only difference between arithmetic and geometric weights would be slightly different coefficients on $\hat{\Omega}_t^R$ and $\hat{\Omega}_t^N$.

[9] Ziliak et al. (1999) regress individual real wages on the aggregate and county unemployment rates (with data from the U.S. Panel Study of Income Dynamics), and their results indicate that aggregate unemployment and county unemployment both have significant effects, with the effect of aggregate unemployment occurring contemporaneously and the effect of county unemployment occurring with a lag. Jimeno and Bentolila (1998) find that wages within sectors and regions in Spain are affected by both regional and national variables (i.e., wages and unemployment). In Buettner (1999), regional wages in Germany are found to depend on lagged wages and unemployment in neighboring areas. The results of Elhorst et al. (2005) indicate that wages in eastern Germany are affected both by regional and national unemployment.

[10] According to the U.S. Census Bureau (2000), over the five year periods 1975-1980, 1980-1985, 1985-1990, and 1990-1995, 20.1% of the population moved to a different state, and 20.9% moved to a different county within the same state. Interstate migration is shown by Blanchard and Katz (1992) to depend on differences in state unemployment rates and by Kennan and Walker (2003) to depend on expected income differences. In fact, Blanchard and Katz (1999, p. 72) state that, "labor mobility is a major source of adjustment to state labor market shocks" in the United States.

[11] This assumption means that wages must vary across firms, so that workers cannot infer the average wage from their own wage. For example, it could be assumed that firms make random errors in setting wages, but that the profit-maximizing wage is set on average. These errors may result from firms' lacking perfect information about the level of product demand or about the parameters in their profit functions.

[12] For simplicity it is assumed that ω is the same in forming expectations of both regional and national wages. In reality, however, it is possible that ω will be different in the expressions for Ω_t^R and Ω_t^N. Simulations (similar to the ones in Section 7) indicate that when ω is allowed to differ in the equations for Ω_t^R and Ω_t^N, the wage curve coefficients depend only on the value of regional ω. In addition, it should be noted that Ω could be assumed to depend on the past growth in wages. The reason why the present study uses a specification in which Ω depends on the past level of wages is to obtain a clearer comparison between the wage curve and the Phillips curve.

[13] Gramlich (1983), de Leeuw and McKelvey (1984), and Baghestani (1992) show that survey measures of expected inflation are not unbiased predictors of actual inflation. Batchelor and Dua (1989), Roberts (1997a, 1998), Thomas (1999), and Mankiw et al. (2003) find that errors in survey inflation forecasts are not orthogonal to information available at the time of the forecast. In addition, Roberts (1998) shows that survey forecasts of inflation can be explained by a model in which part of the population has rational expectations and the rest has adaptive expectations.

[14] Blanchard and Katz (1999) derive a Phillips curve from a model in which workers' reservation wages depend on lagged aggregate wages. In Mankiw and Reis (2002) it is demonstrated that a "sticky information" model (in which each period a fraction of firms receives information that enables them to compute optimal prices, while other firms set prices based on out-of-date information) is able to explain output and inflation dynamics better than a sticky price model. Empirical support for the hypothesis that Phillips curves depend partly on lagged inflation comes from Fuhrer (1997), who finds that the hypothesis that expectations are completely rational can be rejected in Phillips curve specifications in which expected inflation depends on a weighted average of lagged inflation and actual future inflation.

[15] In assumption 3, the equation for Ω_t^R is $\Omega_t^R = (\overline{W}_t^R)^{\omega}(\overline{W}_{t-1}^R)^{1-\omega}$. Since the average regional wage equals the wage of a representative firm in the region, $\overline{W}_t^R = W_t$.

[16] For a log-log specification to provide a better fit than a log-level specification, it is necessary that local unemployment have a smaller effect on the coefficient on $\hat{u}_t^R$ than on the coefficient on du_t^R, but it is not necessary that the coefficient on $\hat{u}_t^R$ be completely unaffected by changes in unemployment. The coefficient on $\hat{u}_t^R$ would be completely unaffected by unemployment if changes in u^R and the ν's exactly offset each other, implying an exact log-log relationship. However, Blanchflower and Oswald (1994) do not state that the relationship between wages and unemployment is exactly log-log. Rather, they find a nonlinear relationship between unemployment and the log of wages, and they use a log-log specification (which they demonstrate fits the data better than a log-level specification) to account for this nonlinearity. In fact, estimated wage equations in Layard et al. (1991) suggest that the relationship is not exactly log-log. When they include both the level and the log of the unemployment rate in the wage equation, the log and the level of unemployment are both significant, although the log has a quantitatively larger effect.

[17] Let W* and u* represent the steady-state values of the wage and unemployment rate. Then $W_t = W^* + dW_t \approx W^*(1+\hat{W}_t)$, and $u_t^R = u^* + du_t^R$. Thus, $\ln(W_t) = \alpha + \hat{\beta}_1 u_t^R + \hat{\beta}_2 \ln(W_{t-1})$ is equivalent to the regression $\ln[W^*(1+\hat{W}_t)] = \alpha + \hat{\beta}_1(u^* + du_t^R) + \hat{\beta}_2 \ln[W^*(1+\hat{W}_{t-1})]$, which can be approximated by $\hat{W}_t = [\alpha - \ln(W^*) + \hat{\beta}_1 u^* + \hat{\beta}_2 \ln(W^*)] + \hat{\beta}_1 du_t^R + \hat{\beta}_2 \hat{W}_{t-1}$. Since $\alpha = \ln(W^*) - \hat{\beta}_1 u^* - \hat{\beta}_2 \ln(W^*)$, the term in square brackets equals 0.

[18] The same value for the long-run elasticity is obtained when the long-run wage is divided by the long-run unemployment rate (where both are expressed in terms of percentage deviations.) This long-run elasticity becomes infinite when ν_1=1, because a demand shock has no long-run effect on unemployment (i.e., the economy is characterized by a natural rate of unemployment), but causes a permanent change in wages.

[19] A simple way to demonstrate that the bargaining and efficiency wage solutions are identical is to substitute (2) into the equation $U = (WL)/N - \overline{U}$ and set dU/dW=0. This maximization problem yields equation (4), which means that firms and workers have the incentive to set the same wage.

[20] For example, suppose that the coefficient on the right-hand side of equation (4) equals 0.5 instead of 1. With the micro-based efficiency function (discussed in Section 5), the coefficient on the unemployment rate in a bargaining model in which $U = W - \overline{U}$ is only 10% lower than the coefficient obtained in a model in which wages are unilaterally set by firms.

While the presence of collective bargaining may not, in itself, have a large effect on the wage curve elasticity, the degree to which regional versus national variables are the target of wage negotiations may affect the value of ν_1, which is a determinant of the wage curve elasticity. (This point was suggested by an anonymous referee.)

[21] Wadhwani and Wall (1991) find an elasticity of productivity with respect to the unemployment rate equal to 0.05 for British manufacturing firms, and Weisskopf (1987) finds that a one percentage point rise in unemployment (e.g., from 5% to 6%) raises labor productivity by approximately 0.01% in the United States and the United Kingdom.

[22] The micro-based efficiency function is reported in equation (9) of Campbell (2006). In choosing parameters for the micro-based efficiency function, it is also necessary to specify values for the interest rate, the proportion of workers who are dismissed, the probability of an exogenous separation, and the ratio between unemployment benefits and average wages. It is assumed that the interest rate is 1% per quarter, the proportion of workers dismissed is 1% per quarter, the probability of an exogenous separation is 3.5% per quarter, and the ratio between unemployment benefits and average wages is 0.35. Values for the exogenous separation probability and the dismissal probability were determined from estimated separation probabilities in several previous studies. The value for the replacement ratio is the average of the replacement rate figures in Appendix Table 1a of Blanchflower and Oswald (2005).

[23] Equations (16a) and (16b) are obtained by setting ν_1 and ν_2 equal to 1 in equations (12a) and (12b). In addition, equations (17a) and (17b) are obtained by setting $\nu_1 = \nu_2 = 1$ in equation (6a).

[24] The fact that $\hat{\beta}_2 = 1$ means that the regression equation can be expressed as $\hat{W}_t - \hat{W}_{t-1} = \hat{\beta}_1 du_t + \varepsilon_t$. Since $\hat{W}_t$ and $\hat{W}_{t-1}$ are the percentage differences in wages from their initial values, the difference between them is the percentage change in wages between period t-1 and period t.

[25] In Campbell and Kamlani's (1997) survey of compensation professionals, the overwhelming majority of respondents expected that workers' effort and morale would be worse if their firm cut wages in the current year than if their firm had historically paid lower wages (controlling for the current value of the wage). Bewley's (1994, p. 10) survey found that "the connection that employers report is between morale and wage decreases, not between morale and wage levels." Kahneman et al. (1986, p. 730) interpret responses to their survey as indicating that "the current wage of an employee serves as reference for evaluating the fairness of future adjustments of that employee's wage." In addition, Clark (1999) finds that reported job satisfaction is more closely related to wage changes than to wage levels.

[26] Predicted coefficients were calculated both with the naïve and micro-based efficiency functions and with specifications in which workers' satisfaction depends linearly and nonlinearly on wage changes. The coefficient lies between -0.713 and -1.10 when efficiency is assumed to depend on absolute wage changes and between -0.870 and -1.22 when it is assumed to depend on relative wage changes. The derivations of the models in which efficiency depends on wage changes are quite complex. For the case in which efficiency depends on relative wage changes, a derivation of the model is available at

www.niu.edu/econ/Directory/campbell.shtml under the heading, "Phillips Curve Model." A dependence of efficiency on wage changes may also raise the coefficient on lagged wages in a wage curve, resulting in a more realistic predicted coefficient than in the baseline case.

[27] The aggregate and regional demand shocks are both assumed to have a mean of 0 and a standard deviation of 0.0075. Regional wages and unemployment in each time period are calculated with an iterative procedure. The paths of wages and unemployment in each region are first calculated from equations (9) and (10) (with the θ_t's depending on the sums of the regional and aggregate shocks) under the assumption that $\hat{\Omega}_t^N$ (expectations of aggregate wages) and du_t^N (aggregate unemployment) equal 0. The calculated values of wages, lagged wages, and unemployment in each region are then averaged to construct new values for $\hat{\Omega}_t^N$ and du_t^N. With these new values of $\hat{\Omega}_t^N$ and du_t^N, new paths for regional wages and unemployment are calculated from equations (9) and (10). The process is continued until the difference between regional wages in each time period converges to within 10^{-6} in successive iterations.

[28] This equation implies that ν_1 and ν_2 would fall from 0.5 to 0.4 in a region whose unemployment rate is five percentage points above the national average.

[29] Equations (6a) and (6b) also make predictions about the values of the coefficients on aggregate wages and unemployment (although empirically estimated wage curves generally include time dummies rather than aggregate variables). If the ν's depend on u^R-u^N, the coefficients on aggregate wages and unemployment may be different from these predicted values. To examine how these coefficients are affected by this dependence, simulated data were used in a regression of regional wages on regional unemployment, lagged regional wages, aggregate unemployment, and expected aggregate wages. With the log-level regression, the average coefficients on aggregate wages and unemployment are close to their predicted values. With the log-log regression, the coefficients are very sensitive to the specification for aggregate unemployment. If aggregate unemployment is entered as either a level or a log, the coefficients on aggregate wages and unemployment are not close to their predicted values, and the R^2 is relatively low. (In fact, consistent with Blanchflower and Oswald (1994, p. 212), the average coefficient on the log of aggregate unemployment is positive.) However, when the level and square of aggregate unemployment are included, the average coefficients are much closer to their predicted values, and the average R^2 is 0.999. These results suggest that the relationship between regional wages and aggregate unemployment is nonlinear, but that the log of aggregate unemployment does not effectively capture the nonlinearity.

[30] The reasons why this equation has a perfect fit are that the model is linearized around its steady-state equilibrium and that, on average, firms in a region are assumed to operate exactly on their labor demand curves in each period. Obviously, actual economies are probably nonlinear, and it is unlikely that firms will operate exactly on their labor demand curves, even when aggregated over an entire region. Thus, the perfect fit in this model should not be taken to imply that wage curves from actual economies should perfectly fit the data on wages and unemployment. However, actual wage curves estimated with average regional wages often do exhibit R^2's above 0.99. (See, for example, Tables 4.26-4.29 of Blanchflower and Oswald (1994).)

Table 1
Estimated wage equations
Baseline parameters: ν_1=0.5, ν_2=0.5, ω=0.5, u=0.06, e=0.8, e_W=0.8, $e_u(u/e)$ =0.05.

	Naïve efficiency function			Micro-based efficiency function		
	$\hat{\beta}_1^*$	$\hat{\beta}_2$	Long – run elasticity	$\hat{\beta}_1^*$	$\hat{\beta}_2$	Long – run elasticity
Baseline	-0.0750	0.333	-0.1125	-0.0499	0.333	-0.0748
ω=0.25	-0.0643	0.429	-0.1125	-0.0428	0.429	-0.0748
ω=0.75	-0.0900	0.200	-0.1125	-0.0599	0.200	-0.0748
u=0.045	-0.0750	0.333	-0.1125	-0.0429	0.333	-0.0643
u=0.075	-0.0750	0.333	-0.1125	-0.0562	0.333	-0.0843
e=0.70	-0.0810	0.333	-0.1214	-0.0519	0.333	-0.0779
e=0.85	-0.0725	0.333	-0.1088	-0.0480	0.333	-0.0720
$e_u(u/e)$ =0.04	-0.0600	0.333	-0.0900	-0.0473	0.333	-0.0709
$e_u(u/e)$ =0.06	-0.0900	0.333	-0.1350	-0.0528	0.333	-0.0791
ν_1=0.3	-0.0662	0.176	-0.0804	-0.0440	0.176	-0.0534
ν_1=0.7	-0.0865	0.538	-0.1875	-0.0576	0.538	-0.1247
ν_2=0.3	-0.0450	0.333	-0.0675	-0.0299	0.333	-0.0449
ν_2=0.7	-0.1050	0.333	-0.1575	-0.0698	0.333	-0.1048
$\nu_1=\nu_2$=0.3	-0.0397	0.176	-0.0482	-0.0264	0.176	-0.0321
$\nu_1=\nu_2$=0.7	-0.1211	0.538	-0.2625	-0.0806	0.538	-0.1746
ν_1=0.6, ν_2=0.4	-0.0643	0.429	-0.1125	-0.0428	0.429	-0.0748

Table 2a*
Estimated wage equations
Dependent variable: regional wages

	1	2	3	4
du_t^R / u^*	-0.0499 (-0.0499, -0.0499)	-0.0703 (-0.0653, -0.0718)		
$\ln[u^* + du_t^R]$			-0.0399 (-0.0166, -0.0476)	-0.0641 (-0.0449, -0.0734)
$\hat{W}_{t-1}$	0.333 (0.333, 0.333)		0.435 (0.327, 0.701)	
Long-run elasticity	-0.0748 (-0. 0748, -0. 0748)	-0.0703 (-0.0653, -0.0718)	-0.0704 (-0.0554, -0.0805)	-0.0641 (-0.0449, -0.0734)
R^2	1.000 (1.000, 1.000)	0.990 (0.980, 0.998)	0.993 (0.979, 0.999)	0.975 (0.924, 0.992)
# obs.	200	200	200	200

* The top number is the average value across all 50 simulations, and the numbers in parentheses are the lowest and highest values (in absolute values) in the simulations.

Table 2b*
Estimated wage equations
Dependent variable: regional wages, model in which $v_{1,i,t} = v_{2,i,t} = 0.5 - 2(du_{i,t}^R - du_t^N)$

	1	2	3	4
du_t^R / u^*	-0.0433 (-0.0284, -0.0495)	-0.0689 (-0.0552, -0.0766)		
$\ln[u^* + du_t^R]$			-0.0470 (-0.0426, -0.0494)	-0.0679 (-0.0642, -0.0713)
$\hat{W}_{t-1}$	0.421 (0.333, 0.553)		0.350 (0.325, 0.394)	
Long-run elasticity	-0.0749 (-0.0600, -0.0845)	-0.0689 (-0.0552, -0.0766)	-0.0723 (-0.0685, -0.0759)	-0.0679 (-0.0642, -0.0713)
R^2	0.994 (0.984, 0.999)	0.977 (0.955, 0.990)	0.999 (0.996, 0.9997)	0.988 (0.979, 0.996)
# obs.	200	200	200	200

* The top number is the average value across all 50 simulations, and the numbers in parentheses are the lowest and highest values (in absolute values) in the simulations.

Table 2c*
Estimated wage equations
Dependent variable: aggregate wages

du_t	-2.49 (-2.49, -2.49)
$\hat{W}_{t-1}$	1.00 (1.00, 1.00)
R^2	1.00 (1.00, 1.00)
# obs.	20

* The top number is the average value across all 50 simulations, and the numbers in parentheses are the lowest and highest values (in absolute values) in the simulations.

Table 2d*
Estimated wage equations
Dependent variable: regional wages, model in which
$\%\Delta N_{i,t} = 0.013(\hat{W}^R_{i,t-1} - \hat{W}^N_{t-1}) - 0.546(du^R_{i,t-1} - du^N_{t-1})$

	1	2	3	4
du^R_t / u^*	-0.0499 (-0.0499, -0.0499)	-0.0639 (-0.0592, -0.0676)		
$\ln[u^* + du^R_t]$			-0.0485 (-0.0461, -0.0509)	-0.0625 (-0.0561, -0.0668)
$\hat{W}_{t-1}$	0.333 (0.333, 0.333)		0.341 (0.321, 0.361)	
Long-run elasticity	-0.0748 (-0.0748, -0.0748)	-0.0639 (-0.0592, -0.0676)	-0.0735 (-0.0696, -0.0775)	-0.0625 (-0.0561, -0.0668)
R^2	1.00 (1.00, 1.00)	0.983 (0.961, 0.997)	0.999 (0.996, 0.9998)	0.980 (0.952, 0.997)
# obs.	200	200	200	200

* The top number is the average value across all 50 simulations, and the numbers in parentheses are the lowest and highest values (in absolute values) in the simulations.