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The Journal of Political Economy, Vol. 99, No. 4. (Aug., 1991), pp. 665-688.

The Effect of Implicit Contracts on the Movement of Wages over the Business Cycle: Evidence from Micro Data

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In this paper we address the question of whether wages are affected by labor market conditions in a manner more consistent with a contract approach than with a standard spot market model. From a simple implicit contract model, we derive implications about the links between wages and past labor market conditions. Using individual data from the Current Population Survey and the Panel Study of Income Dynamics, we find that an implicit contract model with costless mobility describes these links better than either a simple spot market model or an implicit contract model with costly mobility.

I. Introduction

In this paper we address the question of whether wages are affected by labor market conditions in a manner more consistent with a con-

Special thanks to David Card for guidance on this paper. We also thank Orley Ashenfelter, Dwayne Benjamin, Ben Bernanke, Dexter Chu, Bob Gibbons, Kevin Lang, Thomas Lemieux, Phil Levine, Jacques Robert, and Andy Weiss for helpful discussions. DiNardo would like to thank the Lynde and Harry Bradley Foundation and the Industrial Relations Section at Princeton University for financial support. Beaudry would like to acknowledge financial support from the Fonds pour la Formation de Chercheurs et l'Aide à la Recherche du Quebec.

[*Journal of Political Economy*, 1991, vol. 99, no. 4]

tract approach than with a standard spot market model. In particular, we consider whether the history of labor market conditions experienced by workers affects their current wage. We develop a simple contract model to derive some testable implications about wage determination. When workers are not mobile between employers, our contract model predicts a negative correlation between the unemployment rate at the time the worker was hired and his or her current wage. On the other hand, if workers are very mobile, our model predicts that the wage should be correlated with the best labor market conditions observed since the worker was hired. In both cases, these predictions differ from those of a simple spot market model since a spot market model implies that only current labor market conditions affect current wages.

The contract model we develop adheres to the supply and demand framework of the standard spot market model except that it is the contract wage, and not the current wage, that adjusts to competitive forces. The intuition behind the predictions of our model is straightforward. With limited mobility, contract wages are negotiated once at the beginning of the contract, and hence labor market conditions at the time of the contract matter. When workers are mobile, wages are negotiated at the beginning of the contract, but when economic conditions improve, they must be revised upward to prevent the worker from being bid away by other firms.

Using individual data from the Current Population Survey and the Panel Study of Income Dynamics, we find that an implicit contract model with costless mobility describes wage determination better than either a spot market approach or an implicit contract model with costly mobility. That is, current wages are found to be negatively correlated with the lowest unemployment rate realized since workers began with their present employer, and once we control for this effect, the contemporaneous unemployment rate no longer significantly affects wages. Moreover, we find that every percentage increase in the unemployment rate is associated with a 3–7 percent drop in entry-level contract wages.

We believe that this paper potentially contributes to two different literatures. First, this paper makes a contribution to the debate on the empirical importance of contracts in the labor market. For example, papers by Azariadis (1975) and Harris and Holmstrom (1982) have suggested that the existence of contracts can explain some of the puzzles about the functioning of labor markets. On the other hand, empirical work (see Brown and Ashenfelter 1986; MaCurdy and Pencavel 1986; Abowd and Card 1987) has generally found only mixed support for contract models. This paper adds to this literature by developing a robust implication of contract models for which we find strong evidence.

Second, equilibrium models of the business cycle (e.g., Lucas 1975; Kydland and Prescott 1982; Long and Plosser 1983) suggest that variations in employment can be described by equilibrium models of the labor market. As a consequence, much empirical work has concentrated on establishing the extent of the comovement between wages and employment with micro data. For example, Altonji (1986) has examined the importance of intertemporal substitution, while Bils (1985) and Barsky and Solon (1989) have examined comovements between wages and unemployment. In reviews of this evidence, it is often argued that the extent of this comovement is not sufficient to constitute strong support for these models. Our work suggests that this conclusion may be premature. In particular, when appropriate care is taken in incorporating contractual considerations,[1] we find wages to be much more sensitive to labor market conditions than most previous studies.

The paper is organized as follows. In Section II, we present a simple equilibrium model of the labor market in which contracts emerge as a means to insure workers from aggregate risks. This model provides us with predictions about the link between wages and past labor market conditions that are the basis of our empirical investigation. In Section III, we describe the data we use, and in Section IV, we examine the basic predictions of our model. In Section V, we examine the robustness of our results across industries and consider additional implications of the contract model to parameterize the cross-industry variation in our results. Finally, Section VI presents concluding comments.

II. Derivation of the Link between Wages and Labor Market Conditions in a Contractual Economy

Consider an economy populated with risk-neutral entrepreneurs and risk-averse workers. The economy produces only one good, and the worker's utility per period associated with the consumption of c units of the good is given by $U(c)$. Both types of agents have a discount factor equal to β, and the probability that an agent will die in any given period is $1 - \mu$. Each of the entrepreneurs is assumed to have access to a technology that requires one worker. The quantity of

[1] Barro (1977) emphasized the importance of contractual considerations in interpreting the lack of substantial variation in wages over the business cycle.

output from this technology is given by $\Phi(t)$, where $\Phi(t)$ represents the state of labor productivity at time t. For now, assume that the randomness in labor productivity is well approximated by the following AR(1) process (Φ^* is the long-term level):

$$\Phi(t) = (1 - \alpha)\Phi^* + \alpha\Phi(t - 1) + \epsilon(t), \quad 0 < \alpha \leq 1, \epsilon(t) \text{ is i.i.d.} \quad (1)$$

When workers do not have access to capital markets, entrepreneurs have incentives to offer employment contracts that protect workers against the risks associated with productivity shocks.[2] Obviously, competition will force such contracts to offer zero expected profits to employers. If both firms and workers can commit to the contract, then in every period the market equilibrium for risk-sharing employment contracts will be the solution to the following program:[3]

$$\max_{\{w_{t+i}\}} \sum_{i=0}^{\infty} (\beta\mu^2)^i E_t[U(w_{t+i})]$$
$$\text{subject to} \sum_{i=0}^{\infty} (\beta\mu^2)^i E_t[\Phi_{t+i} - w_{t+i}] = 0. \quad (\text{P1})$$

The solution to (P1) is well known: the optimal contract is a fixed wage contract conditional on the survival of both parties. The wage paid at time $t + j$ in a contract negotiated at time t is

$$w(t + j, t) = \Phi^* + \frac{1 - \beta\mu^2}{1 - \beta\mu^2\alpha}[\Phi(t) - \Phi^*] \quad \text{for all } t. \quad (2)$$

Note that this wage depends only on the state of technology at time t and is independent of j.

Given this process for the contractual wages, employment will adjust such that the marginal worker will be indifferent between accepting a job today and staying unemployed this period and postponing until next period the decision to take a job (this assumes that some employment occurs in every period). When workers are unemployed, they are assumed to receive a reservation wage denoted $wh(t)$, which represents the marginal value of household production at time t. The equilibrium condition related to this indifference relationship is given by

$$U(wh(t)) + \beta\mu E\left[\frac{V(w(t + 1, t + 1), \Phi(t + 1))}{\Phi(t)}\right] = V(w(t, t), \Phi(t)). \quad (3)$$

[2] See Rosen (1985) for a survey of the implicit contract literature.
[3] The possibility of temporary layoffs is excluded.

The expression $V(w, \Phi(t))$ represents the discounted expected utility associated with having a job with the contract wage equal to w when the state of technology is $\Phi(t)$.

Equation (3) states that the expected discounted value of staying unemployed today, receiving $wh(t)$, and accepting a job tomorrow must be equal to the value of accepting a job today. Using equations (1)–(3) to solve for the equilibrium relationship between the contract wage and the reservation wage and assuming that $U(\,) = \log(\,)$, Appendix A shows that this results in

$$\log[w(t + j, t)] = \Omega_1 + \frac{1 - \beta\mu^2}{1 - \beta\mu^2\alpha}\log[wh(t)]. \tag{4}$$

Equation (4) states that the time $(t + j)$–period wage paid to a worker who began his job at time t depends positively on the reservation wage of the marginal worker employed at time t. Given the general equilibrium nature of the problem, this reservation wage represents the marginal value of household production and therefore should be negatively related to the fraction of workers remaining in that sector. Consequently, it is reasonable to assume that the reservation wage of the marginal worker changes with the participation rate, $l(t)/L(t)$, as given by[4]

$$\ln[wh(t)] - \ln[wh(t - 1)] = \frac{(1 - \theta)[l(t) - l(t - 1)]}{L(t)}, \quad 0 < \theta < 1. \tag{5}$$

Substituting equation (5)[5] into equation (4) results in

$$\log[w(t + j, t)] = \Omega_1 + \Omega_2\left[1 - \frac{l(t)}{L(t)}\right], \tag{6}$$

where

$$\Omega_2 = \frac{-(1 - \theta)(1 - \beta\mu^2)}{1 - \beta\mu^2\alpha} < 0.$$

The advantage of equation (6) over equation (4) is that it provides us with an empirically testable expression of the link between wages

[4] For example, this would be the case if the household sector functions as a productive sector with decreasing returns to labor. See Beaudry and DiNardo (1989) for a more explicit derivation.

[5] Equation (5) implies that the reservation wage satisfies

$$\ln[wh(t)] = A - (1 - \theta)\left[1 - \frac{l(t)}{L(t)}\right],$$

where A is determined by an initial condition. Note that if A shifts over time (shifts in the labor supply function), it will cause Ω_1 to shift. If these shifts are independent of the temporary changes in productivity, the estimation of (6) by ordinary least squares (OLS) would cause the estimate of Ω_2 to be biased toward zero.

and labor market conditions in a contractual economy. Until further discussion, we shall refer to $1 - [l(t)/L(t)]$ as the unemployment rate.

Equation (6) indicates that the tighter the labor market conditions the year one entered into a job (i.e., the lower the "unemployment" rate), the lower the wage throughout this job. This relationship is the result of the adjustment of the whole employment contract to supply and demand conditions when the labor market functions as a market for contracts. Moreover, this relationship differentiates a contract model from a spot market model since in the latter case it is only the contemporary unemployment rate that should affect wages.

A. Extension to Risk-sharing Contracts with Mobile Workers

One of the assumptions used to derive equation (6) is that workers can commit not to quit a job even though employment contracts offered on the market may be better than the one at hand. We shall call such a situation the case of limited labor mobility. However, when job mobility is costless for workers,[6] the only feasible contracts to which they can commit themselves are those in which it is never profitable for another employer to bid them away. Therefore, contracts must render nonpositive expected profits for the employer in every period and in every state (otherwise the workers will be bid away). The conditions imposed on a contract in order to satisfy the absence of "bidding-away" opportunities are given by the following inequalities:

$$E\left[\sum_{i=j}^{\infty} (\beta\mu^2)^{i-j}[\Phi_{t+i} - W_{t+i}(\Phi^{t+i}) \mid \Phi_{t+j}]\right] \leq 0 \qquad (7)$$

$$\text{for all } j = 1, \ldots, \infty \text{ and all realizations of } \Phi^{t+j}.$$

The relevant contracting program when mobility is costless for workers must therefore take these constraints into account; that is, the constraints given by (7) must be added to the program (P1) in order to define the new risk-sharing problem.

Notice that in the inequalities given by (7), the wage $W_{t+j}(\Phi^{t+j})$ represents the wage paid in period $t + j$ after a history of technological shocks $\Phi^{t+j} = (\Phi_t, \Phi_{t+1}, \ldots, \Phi_{t+j})$ and for a job that began at time t.

Harris and Holmstrom (1982) have analyzed the optimal form of risk-sharing contracts for a situation very similar to the one at hand. The main formal difference between the two problems is that the

[6] Implicit is the assumption that a worker cannot post a bond.

time horizon is finite in the Harris and Holmstrom paper, while it is infinite here.[7] As can be expected, the form of the optimal contract is not affected by this extension. Therefore, as in the Harris and Holmstrom characterization, the optimal zero-profit risk-sharing contract satisfying the non-bidding-away constraints is given by

$$W_{t+j}(\Phi^{t+j}) = \max\{W_{t+j-1}(\Phi^{t+j-1}), X(\Phi_{t+j})\} = \max\{X(\Phi_{t+i})\}_{i=1}^{j}. \quad (8)$$

The function $X(\Phi_{t+i})$ represents the initial wage paid in a contract negotiated in state Φ_{t+i} and is equal to the average expected productivity conditional on $\{\Phi_{t+i} \ldots \Phi_t\}$ being below Φ_t since any realizations of Φ_t must give zero expected profits. The wage contract defined by (8) is often referred to as a downwardly rigid contract. Under such a contractual arrangement, a worker's contract wage is adjusted to match the contemporaneously negotiated first-period wage, $X(\Phi_{t+j})$, whenever the latter is above the former. This adjustment is undertaken so that workers do not quit because of better working conditions offered elsewhere.[8]

Given this downwardly rigid contract structure, we now proceed to link the predicted wage payments with observed labor market conditions. As discussed in Appendix B, when the reservation wage is negatively related to the unemployment rate, as in equation (5), a market equilibrium relation similar to equation (3) ensures that (8) can be rewritten as

$$\begin{aligned} W_{t+j}(\Phi^{t+j}) = W(t+j, t) &= \max\left\{k\left[1 - \frac{l(t+i)}{L(t+i)}\right]\right\}_{i=0}^{j}, \quad k'(\cdot) < 0, \\ &\approx k_0 - k_1 \min\left\{1 - \frac{l(t+i)}{L(t+i)}\right\}_{i=0}^{j}, \quad k_1 > 0. \end{aligned} \quad (9)$$

Equation (9) provides us with a simple prediction about the relationship between wage payments and labor market conditions for a competitive labor market with mobile risk-averse workers. In effect, mobility implies that contractual wage payments should depend on the

[7] In Harris and Holmstrom, the Φ's represent an inference on a worker's intrinsic productivity.

[8] The explicit form of the function $X(\cdot)$ is

$$X(\Phi_t) = \frac{\Phi_t + \sum_{i=1}^{\infty} (\beta\mu^2)^i \text{Prob}(w_i|\Phi_t) E[(\Phi_{t+i})|w_i, \Phi_t]}{1 + \sum_{i=1}^{\infty} (\beta\mu^2)^i \text{Prob}(w_i|\Phi_t)},$$

where w_i is defined as the event $(\Phi_{t+i} \leq \Phi_t, \Phi_{t+i-1} \leq \Phi_t, \ldots, \Phi_{t+1} \leq \Phi_t)$.

most favorable labor market condition observed since one has begun one's job. This prediction contrasts with both that implied by a spot market model and that implied by a contract model with costly mobility and therefore provides easily testable implications of the Harris and Holmstrom theory.

III. The Data

The data we use to investigate whether the labor market functions more like a contract market than a spot market are the Panel Study of Income Dynamics (PSID) and the 1979 and 1983 Pension Supplement of the Census Bureau's May Current Population Survey (CPS). Though these data sets are well known to empirical investigators, a short discussion of aspects relevant to this study is in order.

The primary advantage of the PSID is that it is a panel and makes it possible for researchers to follow individuals over time. Its primary drawbacks are its small size (in 1984 we are left with fewer than 1,957 individuals) and its poor recording of job tenure. In some years tenure is not recorded, and in several years there is confusion over whether the question refers to years in one's present position or years with present employer. This second drawback is somewhat troublesome since it is the tenure variable that allows us to construct measures of market conditions in the first year of the job. Altonji and Shakotko (1987) and Topel (1989) use fairly elaborate procedures to correct this problem, and we use a similar method in this paper.[9] As it turns out, our results are not sensitive to our treatment of this problem.

The CPS data set has two principal features that make it superior to the PSID for our present purposes. First, it is large: after various deletions, we are still left with more than 9,200 observations in each year. Second, since the question on tenure is in the Pension Supplement, it would appear to be better posed than the question in the PSID. The major drawback of the CPS data is that we are not able to follow the same individuals over time.

Some summary statistics for the 1979 and 1983 CPS samples can be found in the first column of table 1. The CPS sample includes males aged 21–64 in the Pension Supplement of the May CPS who

[9] We constructed the tenure data as follows: for each individual, we started in 1984 and forced observations on tenure in previous years to agree. Then we changed any remaining unassigned observations by beginning anew with 1983, and we continued until all observations were consistent across years. In our earlier working paper (Beaudry and DiNardo 1989), we compared the actual measure and our constructed measure and used instrumental variables procedures, all to very little effect, on the estimate we examine in this paper. Following Topel (1989), we also forced age to be consistent across years.

TABLE 1

SELECTED SAMPLE MEANS

	CPS (1979, 1983)	PSID (1976–84)
Average log weekly earnings (1967 dollars)	4.86 (.004)	. . .
Average log hourly earnings (1967 dollars)	. . .	1.12 (.004)
Highest grade completed	12.82 (.022)	11.98 (.022)
Age − school − 5	21.21 (.090)	20.87 (.097)
Union status	.342 (.003)	.29 (.003)
Tenure*	8.337 (.059)	83.03 (.659)
Nonwhite	.097 (.002)	.322 (.003)
Ever married	.907 (.002)	.854 (.003)
SMSA	.556 (.004)	.527 (.004)
Unemployment rate at start of job	4.778 (.013)	4.676 (.013)
Minimum rate since start of job	4.045 (.014)	4.181 (.013)
1 − (emp/pop) ratio at start of job	22.34 (.021)	22.49 (.025)
Minimum 1 − (emp/pop) ratio since start of job	22.01 (.023)	22.24 (.025)
	Number of Observations	
1976		1,958
1977		2,130
1978		2,262
1979	9,422	2,376
1980		2,497
1981		2,433
1982		2,236
1983	9,286	2,110
1984		1,957

* Measured in years for the CPS and in months for the PSID.

had positive, untruncated observations of the weekly wage, who started their job after 1947, and who had no missing data. We choose to work with the weekly wage, which is recorded for salaried workers, and we use the product of usual weekly hours and usual hourly earnings for hourly workers for those who did not report a weekly wage. We choose to work with this measure instead of annual hours divided by annual earnings since the hours reports of hourly workers are likely to be better than the hours reports of salaried workers (see Bound et al. [1989] for a discussion of measurement error).

The same statistics for the PSID sample can be found in the second column of table 1. The sample includes males aged 21–64 who had positive, untruncated observations of the average hourly earnings variable and who started their job after 1947. The samples look roughly similar to the CPS samples for the years in common, although schooling and tenure are somewhat lower. Part of the reason is that we include individuals drawn from the Survey of Economic Opportunity (SEO) in our PSID sample.[10] We choose to work with the average hourly earnings variable since in the PSID it is the most carefully edited and checked of the wage measures. It has the disadvantage of being an hours-weighted measure of the wage on all jobs. The wages in both the PSID and the CPS are deflated by the consumer price index (1967 dollars).

A. *Simple Tests of the Implicit Contract Model*

The theory outlined in Section II has the implication that in a contractual labor market, if workers are immobile, wages should be related to the opportunities available at the time each worker was hired. On the other hand, if workers are perfectly mobile between jobs, the contract approach suggests that current wages should be related to the best labor market conditions observed since one started one's current job. Both these implications contrast with that of a spot market model, where current wages are related only to contemporaneous market conditions. Equation (10), which is the basis of our empirical examination, encompasses all three of these models:

$$\ln w(i, t + j, t) = X_{i,t+j}\Omega_1 + \Omega_2 C(t,j) + \epsilon_{i,t+j}, \tag{10}$$

$$C(t,j) = \begin{cases} U_{t+j} & \text{spot market model} \\ U_t & \text{contracts with costly mobility} \\ \min\{U_{t-k}\}_{k=0}^{j} & \text{contracts with costless mobility.} \end{cases}$$

That is, the wage in period $t + j$ for an individual i who began the job in period t is a function of his individual characteristics X_i, an appropriate labor market condition link variable $C(t, j)$, and an error term, where only $C(t, j)$ depends on the particular model. Note that the unemployment rate at time t is denoted U_t.

The vector of controls, **X**, used for estimation includes experience, experience squared, schooling, tenure, and dummies for industry,

[10] Since the results for the SEO subsample looked no different from those for the non-SEO subsample, we opted for a larger sample.

region, race, union status, marriage, and standard metropolitan statistical area (SMSA) (see the tables below for more details).[11]

Strictly speaking, equations (6) and (9) suggest using one minus the employment to population ratio as the measure of the unemployment rate. Whether a worker is looking for work or not is immaterial in the context of the model described above. However, almost all previous studies (see, e.g., Bils 1985; Barsky and Solon 1989) have used the reported unemployment rate as a measure of labor market tightness. Largely to facilitate comparison with this substantial literature and to be able to work with industry-specific measures of labor market tightness, we too shall work with reported unemployment rates. However, as a check on the robustness of the results, we also present some estimates using the employment to population ratio.

It is finally worth commenting on our strategy to focus mainly on the specific implications of the model in lieu of a more general treatment of the effect of all past labor market conditions on wages. In particular, consider the assumption that productivity follows an AR(1) process. In our setup, this assumption implies that the unemployment rate series also follows an AR(1) process and is therefore a sufficient statistic for the labor market condition in a given period. Most other assumptions regarding the stochastic component of productivity would lead to the inclusion of more unemployment rates in the empirical specification. However, since the average length of a job (censored spells included) is about 8 years, the three measures we consider—the contemporaneous unemployment rate, the unemployment rate at the start of the job, and the minimum rate since the start of the job—should go a long way to span the set of sufficient statistics for the history of labor market conditions under alternative assumptions.

IV. Estimates Using Aggregate Unemployment Rates

Table 2 presents the core results of the paper. The first 10 rows present estimates from the PSID and the next three rows use data from the CPS. In all the regressions presented in this table, the "unemployment rate" we use is the economywide measure for males 20 years old and older.

[11] In the tables that follow we adopt the same set of control variables. However, we experimented with other specifications that included quadratic terms of the unemployment rate, interactions of tenure with the unemployment rate, interactions of the unemployment rate with potential experience, various splines for tenure, and removal of age-specific means from the data, among others; the reported results are uniformly quite robust.

TABLE 2

RESULTS FROM PSID AND CPS

	Contemporaneous Unemployment Rate	Unemployment at Start of Job	Minimum Rate since Start of Job	Data
1.	−.020 (.002)	...	...	PSID (levels)
2.	...	−.030 (.002)	...	PSID (levels)
3.	...	...	−.045 (.003)	PSID (levels)
4.	−.010 (.002)	−.025 (.002)	...	PSID (levels)
5.	−.001 (.002)	...	−.044 (.003)	PSID (levels)
6.	.000 (.002)	.013 (.004)	−.059 (.006)	PSID (levels)
7.	−.014 (.002)	...	...	PSID (fixed effect)
8.	...	−.021 (.003)	...	PSID (fixed effect)
9.	...	...	−.029 (.003)	PSID (fixed effect)
10.	−.007 (.0025)	−.006 (.007)	−.029 (.008)	PSID (fixed effect)
11.	...	−.017 (.002)	...	CPS (levels)
12.	...	...	−.031 (.003)	CPS (levels)
13.	...	.004 (.003)	−.036 (.005)	CPS (levels)
		Pooled PSID and CPS*		
14.	...	−.021 (.003)	...	CPS nonunion
15.	...	−.010 (.003)	...	CPS union
16.	...	...	−.034 (.004)	CPS nonunion
17.	...	...	−.022 (.005)	CPS union
18.	...	−.018 (.003)	...	CPS using 1 − (emp/pop)
19.	...	...	−.032 (.003)	CPS using 1 − (emp/pop)
20.	...	.030 (.006)	−.065 (.007)	CPS using 1 − (emp/pop)
21.	...	−.024 (.002)	...	PSID using 1 − (emp/pop)
22.	...	...	−.032 (.002)	PSID using 1 − (emp/pop)
23.	.005 (.003)	.041 (.007)	−.080 (.008)	PSID using 1 − (emp/pop)

NOTE.—Standard errors are in parentheses. For the PSID estimates, the dependent variable is log average hourly earnings (1967 dollars). Other regressors are experience, experience squared, tenure, and schooling and dummies for nonwhite, SMSA, union, marriage, five regions, and 13 industries. There are 19,958 observations in the pooled sample. For details on the CPS estimates, see table 3. The standard errors in rows 7–10 are conventional generalized least squares estimates; the rest are heteroskedasticity consistent.

* All coefficients are allowed to vary between the union and nonunion samples. Standard errors are consistent under arbitrary forms of heteroskedasticity. Other regressors include potential experience, experience squared, tenure, and schooling and dummies for union, nonwhite, SMSA, four regions, and year. The standard errors for the PSID result from treating the cross sections as independent observations.

Rows 1–3 present estimates of the effect of labor market conditions on wages under the three alternative assumptions about the functioning of the labor market (estimates of Ω_2). Although the size of the coefficient on the minimum unemployment rate variable (the minimum rate since the beginning of the job) is much larger than the two other variables, all three coefficients are negative and significant as predicted by each theory. Note that the coefficient on the contemporaneous rate is of the same order of magnitude as in many previous studies.

Rows 4–6 present estimates for specifications in which we let the theories compete by simply nesting the different measures of the "labor market link" variable in the same regression. Our main finding is that the contract model with costless mobility seems to fit the data the best, while the spot market model does the poorest. In particular, the specification in row 5 indicates that, once we control for the minimum unemployment rate since one began the job, the effect of the contemporaneous unemployment rate is virtually zero (and is precisely estimated). Moreover, the minimum unemployment rate variable clearly dominates the two other variables when all three measures are allowed to compete.

In rows 7–10, most of the previous coefficients are reestimated using the same data, but now the data have person-specific means removed. We do this to check whether our results can be explained by individual-specific, time-invariant heterogeneity. The results are similar to those in levels except that the coefficients are uniformly smaller.[12] The contract model with costless mobility still seems to summarize the data best, although the small effect of the contemporaneous labor market on wages is significant even when all three measures are allowed to compete.

In rows 11–13, we present estimates using the CPS data for 1979 and 1983. With only two cross-sections it is unreasonable to estimate the effect of contemporaneous labor market conditions on wages; therefore, in all three regressions we simply include a year dummy to control for any contemporaneous effect of labor market conditions. These results with the CPS again indicate the importance of the link between wages and the best labor market conditions since one was hired. When both contracting models are allowed to compete, the minimum unemployment rate variable captures the effect of past labor market conditions on wages better than simply the unemployment rate at the time one was hired.

[12] Using PSID data for 1968–84, Barsky and Solon (1989) estimate the effect of contemporaneous labor market conditions to be −.0126, in comparison with our estimate of −.014.

Some further evidence on the robustness of our results is presented in rows 14–23. In rows 14 and 15 we look at the union and nonunion subsamples of the CPS. In both subsamples our proposed measures are estimated precisely, although there is evidence that labor market tightness exerts a greater influence on nonunion wages.[13] In rows 18–23 we replace the unemployment rate for males over 20 with one minus the employment to (active) population ratio for this same group. As discussed above, these alternative measures are very highly correlated with the measures constructed from the unemployment rate data. It is therefore not surprising that the results look very similar, although the predicted impact of labor market tightness on wages is somewhat larger for the oldest-vintage workers in our sample. Similar too is the pattern of results. The minimum "one minus the employment to population ratio" since the start of a job again appears to be the robust measure of the three.

Overall, these results indicate that the contemporaneous unemployment rate is not a robust measure of the extent to which labor market conditions affect wages, whereas the minimum unemployment rate since one began a job is more so. Therefore, the results are supportive of the idea that the labor market may function more like a contract market than a spot market and, in particular, like a contract market for mobile workers.[14] Moreover, the many other specifications we tried confirmed the robustness of the effect on wages of the minimum unemployment rate variable. For example, even when we simultaneously allow for an unrestricted tenure profile (years of tenure dummies) and an unrestricted experience profile (years of experience dummies), we still find this effect to be significant (the coefficient is $-.033$; the standard error is .003 with the PSID).[15]

V. Estimates by Industry

The previous section investigated implications of our simple contract model using a pooled sample of all individuals. This assumes that all

[13] Using data from the United Kingdom and contemporaneous county unemployment rates, Blanchflower, Oswald, and Garret (1988) find that the wage–unemployment rate elasticity is smaller for unionized establishments. McConnell (1989) also finds evidence of a small wage–unemployment rate elasticity in the union sector in the United States.

[14] If there are shifts in labor supply, our interpretation of the results remains valid as long as these shifts are uncorrelated with shifts in productivity (see n. 5).

[15] Although we do not present the results, we also experimented with other summary statistics for the history of labor market conditions. Our most extensive experiments used generalized means of the form $M(\lambda) = |(1/N)\,\Sigma\, x_i^{\lambda}|$. As $\lambda \rightarrow -\infty$, $M(\lambda)$ equals the minimum unemployment rate since one started with an employer; as $\lambda \rightarrow \infty$, $M(\lambda)$ equals the maximum unemployment rate since one started with an employer. None of the values of λ we tried was more robust than the measures reported here (we tried 25, 5, 1, 0, -5, and -25).

segments of the labor market behave similarly. In this section we shall examine whether our results are robust or similar across industries.[16] In order to have a reasonable number of observations on different individuals in each industry, we confine our estimation of industry-specific effects to the CPS data. As noted above, this restricts us from estimating the contemporaneous effect of labor market conditions. However, by including a dummy variable for the year of the survey, we can still examine whether past labor market conditions matter for current wages after controlling for arbitrary contemporaneous effects.

Tables 3 and 4 present estimates of Ω_2 for 21 industries for the contract model with costly mobility and the contract model with costless mobility, respectively. For each industry we first estimated equation (9) by OLS, using the aggregate unemployment rate in column 1 and the industry-specific unemployment rate in column 2. We allow other coefficients to vary for each industry to minimize the possibility of biases introduced by other misspecifications. The set of control variables is unchanged.

There are several points worth noting about the results in tables 3 and 4. The estimates of both models have the estimated sign and have a reasonable order of magnitude for almost all industries. In particular, for the costless mobility model, the estimated coefficients for Ω_2 range mostly between $-.03$ and $-.05$ and are significant at conventional levels for 15 industries (with the insignificant coefficients being concentrated within industries with relatively small samples). Furthermore, the robustness of these results across industries militates against an interpretation of our results as merely indicating that industries with high wage differentials are industries that do their hiring in good times.

Notice that the estimates of Ω_2 are in general larger (more negative) but less precisely estimated with the industry-specific unemployment rates than with the aggregate rates. This could be caused by a measurement error problem since the industrial affiliation of an unemployed worker is not always obvious. A possible way to correct for potential biases is to instrument industry rates with the aggregate rate. This is a natural choice for an instrument since perhaps the measurement error in the aggregate rate is uncorrelated with the measurement error in the industry rate; at the same time it is likely to be highly correlated with the actual rate itself. If these conjectures are correct, we expect the coefficients on Ω_2 to be larger after instru-

[16] A state-by-state segmentation would also be appropriate. Unfortunately, we have reliable state unemployment data only back to 1976. Nevertheless, results when we used the state rate and substituted the aggregate rate when it was missing yielded similar estimates.

TABLE 3

Contract Model with Costly Mobility: CPS Estimates by Industry

Industry	Ordinary Least Squares: Aggregate (1)	Ordinary Least Squares: Industry (2)	Instrumental Variables (3)	Hausman Test $\chi^2(1)$ (4)	N (5)
Agriculture	−.006	−.012	−.023	.256	352
	(.017)	(.011)	(.024)		
Mining	−.038	−.014	−.025	.489	373
	(.015)	(.007)	(.017)		
Construction	−.007	−.000	−.013	4.27	1,669
	(.007)	(.003)	(.007)		
Durable manufacturing	−.011	−.003	−.013	2.21	3,624
	(.004)	(.003)	(.007)		
Nondurable manufacturing	−.037	−.025	−.039	.982	1,939
	(.006)	(.005)	(.015)		
Transportation	−.015	−.023	−.019	.005	264
	(.015)	(.016)	(.058)		
Other transportation	−.020	−.026	−.033	.089	889
	(.009)	(.011)	(.027)		
Other utilities	−.001	−.003	−.003	.047	866
	(.010)	(.011)	(.028)		
Wholesale trade	−.021	−.021	−.055	2.49	1,054
	(.009)	(.010)	(.024)		
Retail trade	−.024	−.024	−.060	5.67	1,872
	(.008)	(.010)	(.018)		
Finance, insurance, and real estate	−.013	−.001	−.059	2.73	781
	(.013)	(.020)	(.041)		
Business repair services	−.059	−.095	−.131	.980	674
	(.012)	(.025)	(.044)		
Personal services	−.047	−.069	−.107	.293	208
	(.019)	(.034)	(.078)		
Entertainment	.009	.035	−.048	1.21	148
	(.030)	(.057)	(.094)		
Medical services	−.035	−.072	−.107	.134	149
	(.028)	(.041)	(.105)		
Hospital services	.000	.016	−.018	.272	358
	(.014)	(.024)	(.071)		
Welfare services	−.050	−.078	−.127	.548	253
	(.020)	(.035)	(.075)		
Educational services	−.016	−.013	−.044	1.25	1,261
	(.009)	(.014)	(.032)		
Other professional services	−.034	−.045	−.106	1.78	402
	(.018)	(.032)	(.056)		
Forestry/fishing	.072	.066	.059	.005	62
	(.007)	(.023)	(.092)		
Public administration	−.012	−.028	−.055	24.5	1,491
	(.007)	(.016)	(.017)		
Pooled	−.017	−.007	−.024	18.06	18,711
	(.002)	(.002)	(.004)		
	Test for Constancy of Coefficient across Industries				
$\chi^2(21)$*	45.08	67.25	29.63		
	(.002)	(.000)	(.010)		
Schwartz criterion	206.6	206.6	206.6		

Note.—Standard errors are in parentheses. The estimates in col. 1 use the U.S. aggregate unemployment rate for prime-age males, those in col. 2 use the industry unemployment rate for wage and salaried workers from Citibase (CPS estimates), and those in col. 3 are the industry rates instrumented by the aggregate rate. The test statistics in col. 3 are distributed $\chi^2(1)$ under the null hypothesis that the uninstrumented estimate is consistent. The test statistics in the penultimate row are distributed $\chi^2(21)$ under the hypothesis that the coefficient is constant across industries. All other coefficients are allowed to vary. All the tests and standard errors are consistent under arbitrary forms of heteroskedasticity. Other regressors include potential experience, experience squared, tenure, and schooling and dummies for union, nonwhite, SMSA, four regions, and year. The pooled estimate results from imposing the restriction that the 22 coefficients are constant. One industry grouping with 18 individuals is not presented. The dependent variable is log weekly earnings (1967 dollars).

* Numbers in parentheses in this row are probability values.

TABLE 4

CONTRACT MODEL WITH COSTLESS MOBILITY: CPS ESTIMATES BY INDUSTRY

Industry	Ordinary Least Squares: Aggregate (1)	Ordinary Least Squares: Industry (2)	Instrumental Variables (3)	Hausman Test $\chi^2(1)$ (4)	N (5)
Agriculture	−.028	−.022	−.036	.562	352
	(.021)	(.014)	(.023)		
Mining	−.047	−.017	−.025	.215	373
	(.20)	(.010)	(.020)		
Construction	−.019	−.010	−.021	2.88	1,669
	(.008)	(.005)	(.008)		
Durable manufacturing	−.028	−.018	−.028	1.29	3,624
	(.006)	(.004)	(.010)		
Nondurable manufacturing	−.045	−.047	−.063	.669	1,939
	(.009)	(.009)	(.022)		
Transportation	−.008	−.014	−.015	.000	264
	(.016)	(.028)	(.088)		
Other transportation	−.037	−.055	−.052	.011	889
	(.012)	(.017)	(.033)		
Other utilities	−.013	−.023	−.033	.081	866
	(.014)	(.018)	(.042)		
Wholesale trade	−.031	−.037	−.078	.209	1,054
	(.011)	(.015)	(.090)		
Retail trade	−.030	−.034	−.075	7.59	1,872
	(.010)	(.014)	(.020)		
Finance, insurance, and real estate	−.037	−.077	−.112	.958	781
	(.17)	(.035)	(.051)		
Business repair services	−.66	−.153	−.135	.271	674
	(.016)	(.034)	(.048)		
Personal services	−.055	.107	−.109	.002	208
	(.016)	(.049)	(.085)		
Entertainment	−.019	−.060	−.109	.480	148
	(.044)	(.083)	(.108)		
Medical services	−.030	−.100	−.132	.480	149
	(.036)	(.075)	(.128)		
Hospital services	−.015	−.021	−.056	.059	358
	(.019)	(.039)	(.085)		
Welfare services	−.084	−.180	−.176	.003	253
	(.026)	(.054)	(.091)		
Educational services	−.037	−.062	−.132	1.13	1,261
	(.015)	(.029)	(.048)		
Other professional services	−.039	−.077	−.102	1.47	402
	(.023)	(.051)	(.070)		
Forestry/fishing	.120	.081	.063	.030	62
	(.047)	(.034)	(.106)		
Public administration	−.030	−.055	−.106	1.40	1,491
	(.12)	(.022)	(.048)		
Pooled	−.031	−.022	−.034	7.60	18,711
	(.003)	(.003)	(.005)		
	Test for Constancy of Coefficient across Industries				
$\chi^2(21)$	30.11	67.10	44.50		
	(.089)	(.000)	(.001)		
Schwartz criterion	206.6	206.6	206.6		

NOTE.—See notes to table 3.

mentation. A brief glance through column 3 in both tables 3 and 4 shows that, while the standard errors increase somewhat, the coefficients are almost uniformly more negative once we instrument the industry rate with the aggregate rate.

The estimated coefficients for Ω_2, for each of the three columns taken separately, do not seem to be constant across industries. The test statistic for this hypothesis is given at the bottom of each column, with the p-values never being greater than .01. This cross-industry variation in the estimates will be explored in the following subsection.

Overall, the estimates in tables 3 and 4 indicate that, independent of the exact measure of labor market conditions, past labor market conditions strongly affect wages even after contemporaneous effects are controlled for. This suggests that our observation that a simple spot market model is an inadequate description of the effect of labor market conditions on the wage is quite robust across industries.

Table 5 completes the picture at the industry level by presenting estimates for the nested specification. With aggregate rates, the estimates in table 5 indicate that when both the unemployment rate at the start of a job and the minimum unemployment rate since the start of a job are included in the same regression, the unemployment rate is never both negative and significant at conventional levels, while the minimum rate is generally negative and quite precisely estimated.

A. *A Parameterization of the Cross-Industry Variation of the Contractual Effect on Wages*

Up to this point, we have examined only whether past labor market conditions affect wages. In this subsection we make a preliminary attempt to use the model developed in Section II to make additional predictions about the magnitude of these effects. Recall from equation (6) that the effect of labor market conditions, Ω_2, varied both with the level of persistence of shocks in productivity, α, and with the rate of exogenous breakup, $1 - \mu$. If we view labor markets as being separated by industry, the coefficient Ω_2 in equation (10) needs to be augmented by an industry subscript. While it is possible to estimate these additional parameters by nonlinear methods, consider the following approximation, which is linear in the parameters:

$$\begin{aligned} \ln w(i, t + j, t, h) &= \Omega_1 X_i + \Omega_2(\alpha_h, \mu_h) C(t, j, h) \\ &= \Omega_1 X_i + [\gamma + \phi(1 - \mu_h) + \delta\alpha_h] C(t, j, h) \\ &= \Omega_1 X_i + \gamma C(t, j, h) + \phi(1 - \mu_h) C(t, j, h) \\ &\quad + \delta\alpha_h C(t, j, h). \end{aligned} \tag{11}$$

TABLE 5

NESTING THE TWO CONTRACT MODELS: CPS ESTIMATES BY INDUSTRY

Industry	Unemployment at Start of Job	Minimum Rate since Start of Job	Number of Observations
Agriculture	.049	−.077	352
	(.028)	(.035)	
Mining	−.025	−.022	373
	(.017)	(.029)	
Construction	.021	−.040	1,669
	(.012)	(.015)	
Durable manufacturing	.014	−.042	3,624
	(.006)	(.013)	
Nondurable manufacturing	−.016	−.028	1,939
	(.009)	(.009)	
Transportation	−.022	.012	264
	(.018)	(.026)	
Other transportation	.009	−.046	889
	(.016)	(.021)	
Other utilities	.021	−.036	866
	(.014)	(.020)	
Wholesale trade	−.002	−.029	1,054
	(.014)	(.018)	
Retail trade	−.011	−.019	1,872
	(.014)	(.018)	
Finance, insurance, and real estate	.040	−.080	781
	(.519)	(.029)	
Business repair services	−.041	−.023	674
	(.030)	(.034)	
Personal services	−.030	−.022	208
	(.019)	(.043)	
Entertainment	.100	−.120	148
	(.068)	(.080)	
Medical services	−.043	.012	149
	(.034)	(.046)	
Hospital services	.035	−.053	358
	(.025)	(.019)	
Welfare services	.016	−.102	253
	(.040)	(.052)	
Educational services	.010	−.049	1,261
	(.012)	(.022)	
Other professional services	−.025	−.013	402
	(.025)	(.032)	
Forestry/fishing	.021	.098	62
	(.042)	(.067)	
Public administration	.009	−.039	1,491
	(.010)	(.017)	
Pooled*	.004	−.036	18,711
	(.003)	(.005)	
	Test for Constancy of Coefficient across Industries		
$\chi^2(21)$[†]	34.63	20.15	
	(.031)	(.512)	
Schwartz criterion	206.6	206.6	

NOTE.—Standard errors are in parentheses. The test statistic is distributed $\chi^2(21)$ under the null hypothesis that the coefficient is constant across industries. All other coefficients are allowed to vary. Both the tests and standard errors are consistent under arbitrary forms of heteroskedasticity. Other regressors include potential experience, experience squared, tenure, and schooling and dummy variables for union, nonwhite, SMSA, four regions, and year. The pooled estimate results from imposing the restriction that the 22 coefficients are constant. One industry grouping with 18 individuals is not presented. The dependent variable is log weekly earnings (1967 dollars).

* All other coefficients are free.

† Numbers in parentheses here are probability values.

Remember from equation (10) that $C(t, j, h)$ represents the unemployment rate appropriate to either the no-mobility or costless mobility model (an h subscript is now added to refer to the industry). The added variables $1 - \mu_h$ and α_h represent the rate of exogenous breakup and the persistence of shocks of industry h, respectively. The theory therefore provides a suggestion (or a test) on how to explain the cross-industry variation in Ω_2 observed in the previous section. Again following equation (6), we expect $\phi < 0$ and $\delta < 0$.[17] The intuition for this result is straightforward. If productivity shocks are very persistent, a given deterioration in current market conditions, as expressed by an increase in unemployment, will lead workers to accept a lower contract wage since the outlook associated with staying unemployed is bleak. Similarly, if the exogenous breakup rate is high, a given deterioration in current market conditions will lead workers to accept a lower contract wage since they do not expect to be locked in to the lower wage for very long.

The empirical implementation of (11) is not obvious since it is not easy to obtain measures of μ and α. Our approach is to estimate both $1 - \mu$ and α from the time-series process of annual industry-specific unemployment rates. If the cycle in the unemployment rate is approximately symmetric, the unconditional variance of the unemployment rate is perhaps not too bad an approximation for $1 - \mu$ (we choose to focus on the detrended rate). We considered several statistics to measure persistence, including the variance ratio statistic proposed by Cochrane (1988). Following along the lines of Campbell and Mankiw (1987), we adopt a simple measure that, for the case of an AR(1) process, is merely $\alpha^* = 1/(1 - \rho_1)$, where ρ_1 is the estimated autoregressive parameter from the detrended series.

In table 6 we present the estimates for both contract models. In the first part of the table we present the instrumental variables estimates for both models using as instruments the aggregate unemployment rate and its interaction with $1 - \mu$ and α.[18] The estimate of δ has the predicted sign and is significant; the estimate of ϕ (associated with the breakup rate) has the wrong sign and is imprecisely estimated. For clarity in the interpretation of the results, we present (in addition to our estimates of $1 - \mu$ and α^*, where α^* is the persistence measure, not the AR(1) parameter) the estimated derivatives of the log wage with respect to the relevant unemployment rate variable for nine industry groupings. In each industry the effect is significant, large in magnitude, and quite precise. The estimates range from 0.8

[17] We believe that the restrictions also apply for eq. (9), although we have not been able to prove this under general conditions.

[18] The industry-by-industry estimates are similar when the uninstrumented data are used.

TABLE 6

PARAMETERIZATION OF THE CROSS-INDUSTRY VARIATION (CPS)

Model: $\ln w(i, t + j, t, h) = X_t\beta + \gamma C(t, j) + \phi(1 - \mu_h)C(t, j) + \delta\alpha_h C(t, j)$

	No Mobility	Costless Mobility
$\hat{\gamma}$	.022	−.005
	(.005)	(.013)
$\hat{\phi}$	.003	.005
	(.002)	(.004)
$\hat{\delta}$	−.026	−.026
	(.005)	(.005)

			$\delta \ln w_{h,t+j}/\delta C_{t,j}$	
INDUSTRY	α_h^*	$1 - \mu_h$	Rate at Start of Job	Minimum Rate since Start of Job
Agriculture	2.29	3.47	−.028	−.049
			(.008)	(.008)
Mining	2.19	11.6	−.004	−.009
			(.015)	(.015)
Construction	1.95	10.3	−.002	−.008
			(.014)	(.014)
Durables	1.69	5.93	−.007	−.022
			(.011)	(.011)
Nondurables	2.10	2.44	−.026	−.048
			(.007)	(.008)
Transportation and public utilities	1.90	1.55	−.024	−.047
			(.006)	(.007)
Trade (wholesale and retail)	2.77	1.58	−.046	−.070
			(.007)	(.007)
Finance and services	2.50	.817	−.040	−.066
			(.005)	(.006)
Public administration	3.24	.484	−.061	−.087
			(.006)	(.006)

NOTE.—Except for construction and government, α_h^* (our persistence measure) is calculated from the AR(1) parameters of the detrended annual measures of unemployment for wage and salaried workers. Agriculture and government were calculated from an AR(2) model. The data on unemployment, for the period 1948–88, come from Citibase. The $1 - \mu_h$ (measure of breakup) is the regression variance from the detrending equation with a linear and quadratic time trend. The standard errors for the last two columns do not account for the fact that μ_h and α_h are sample estimates. The estimates of the model are instrumental variables estimates using the aggregate rate, aggregate times $1 - \mu_h$, and aggregate times α_h^* as instruments. The autoregressive parameters were estimated by minimizing the conditional sums of squares.

to 8.7 percent for the costless mobility model and from 0.2 to 6 percent for the no-mobility model. Given the substantial problems in measuring and defining $1 - \mu$ and α, the results are quite surprising. In particular, the fact that δ is significant and has the predicted sign provides some evidence in favor of interpreting wages as the solution to an intertemporal contracting problem. It should be noted, however, that our model explains only a small portion of the unexplained variation across industries in the level of wages and that industry dummies remain jointly significant.

VI. Conclusions

The main result of this paper is that an implicit contract model with costless mobility seems to provide a better framework for describing the link between labor market conditions and wages than a spot market model. In particular, once we control for the best labor market conditions since a worker began a job, as suggested by a modified version of the implicit contract model developed by Harris and Holmstrom (1982), we find that the contemporaneous unemployment rate no longer affects wages. Moreover, the size of our estimates indicates that the labor market, viewed as a market for contracts, is very procyclical even though employed workers are protected against deteriorating labor market conditions. Finally, we also find some evidence that the cross-industry variation in our results conforms to a parameterization suggested by the theory, which we also view as encouraging for contract models.

Appendix A

In this Appendix we derive equation (4) of the text. In order to simplify equation (3), it is helpful to express the value function $V(\cdot, \cdot)$ as the expected utility associated with one's present job plus the expected value associated with losing the job. This expansion is given by

$$V(w, \Phi(t)) = \frac{U(w)}{1 - \beta\mu^2} + \sum_{i=1}^{\infty} \mu(1 - \mu)\beta^i(\mu^2)^i\{E[V(w(t + i), \Phi(t + i)|\Phi(t))]\}. \tag{A1}$$

Since the wage payment $w(t + j, t)$ does not depend on $t + j$, this argument will be suppressed temporarily.

Substituting (A1) into (3) and eliminating terms result in

$$U(wh(t)) = U(w(t)) + \frac{\beta\mu^2}{1 - \beta\mu^2}\{U(w(t)) - E[U(w(t + 1)|\Phi(t))]\}. \tag{A2}$$

Assuming $U(\cdot) = \log(\cdot)$ and using equations (1) and (2) to replace $w(t + 1)$ in equation (A2), we can write

$$\begin{aligned} \log[wh(t)] = {} & \frac{\log[w(t)]}{1 - \beta\mu^2} - \frac{\beta\mu^2}{1 - \beta\mu^2} \\ & \cdot E\left[\log\left[(1 - \alpha)\Phi^* + \alpha w(t) + \frac{(1 - \beta\mu^2)\epsilon(t)}{1 - \beta\mu^2\alpha}\right]\right]. \end{aligned} \tag{A3}$$

The Taylor series expansion of $\log\{(1 - \alpha)\Phi^* + \alpha w(t) + [(1 - \beta\mu^2)\epsilon(t)/(1 - \beta\mu^2\alpha)]\}$ around Φ^* is

$$\begin{aligned} \log\left[(1 - \alpha)\Phi^* + \alpha w(t) + \frac{(1 - \beta\mu^2)\epsilon(t)}{1 - \beta\mu^2\alpha}\right] = {} & \log(\Phi^*) + \frac{\alpha}{\Phi^*}[w(t) - \Phi^*] \\ & + \frac{1}{\Phi^*}\frac{(1 - \beta)\epsilon(t)}{1 - \beta} + Rp, \end{aligned} \tag{A4}$$

where Rp is the residual representing second-order and higher terms. This residual is always negative because $U(\cdot)$ is concave. Although Rp is time varying, we shall assume that it can be well approximated as a constant.

Taking the expectation of (A4), substituting the result into equation (A3), and using the approximation

$$\frac{w(t) - \Phi^*}{\Phi^*} \approx \log[w(t)] - \log(\Phi^*) \tag{A5}$$

give

$$\log[wh(t)] = \frac{1 - \alpha\beta\mu^2}{1 - \beta\mu^2}\log[w(t)] - \frac{\beta\mu^2(1 - \alpha)}{1 - \beta\mu^2}\log(\Phi^*) - \frac{\beta\mu^2 Rp}{1 - \beta\mu^2}. \tag{A6}$$

Rearranging terms results in

$$\begin{aligned}\log[w(t + j, t)] = {} & \frac{1}{1 - \beta\mu^2}[\beta\mu^2(1 - \alpha)\log(\Phi^*) + \beta\mu^2 Rp] \\ & + \frac{1 - \beta\mu^2}{1 - \alpha\beta\mu^2}\log[wh(t)].\end{aligned} \tag{4}$$

The contract wage is now restated in terms of its two arguments.

Appendix B

In order to derive relationship (9), it is useful to rewrite the labor market equilibrium condition given in equation (A1) for the case in which the contract wage satisfies equation (8). This expansion of equation (A1) is given by

$$\begin{aligned}U(wh_t) = U(X(\Phi_t)) + \sum_{\iota=1}^{\infty} (\beta\mu^2)^{\iota}\{ & E[U(\max\{X(\Phi_{t+j})\}_{j=0}^{\iota}) \mid \Phi_t] \\ & - E[U(\max\{X(\Phi_{t+j})\}_{j=1}^{\iota}) \mid \Phi_t]\}.\end{aligned} \tag{B1}$$

As a consequence of the assumption that the Φ's obey an AR(1) process, the right-hand side of equation (B1) can be written as $U(wh(t)) = g(\Phi_t)$. Moreover, since $X(\cdot)$ is a strictly increasing function and the Φ's are positively autocorrelated at all lags, the function $g(\cdot)$ is a strictly increasing function of Φ and hence can be inverted. The state of technology can therefore be expressed as an increasing function of the current reservation wage: $\Phi_t = g^{-1}(U(wh_t))$.

It is now possible to relate wage payments with labor market conditions. Maintaining the assumption that $U(\cdot) = \log(\cdot)$ and using equation (5) to link the unemployment rate with the reservation wage, we can rewrite equation (8) as

$$\begin{aligned} W_{t+j} &= \max\left\{X\left(g^{-1}\left(A - (1 - \theta)\log\left[1 - \frac{l(t + i)}{L(t + i)}\right]\right)\right)\right\}_{\iota=0}^{j}, \\ W(t + j, t) &= \max\left\{k\left(1 - \frac{l(t + i)}{L(t + i)}\right)\right\}_{i=0}^{j}, \quad k'(\cdot) < 0.\end{aligned} \tag{B2}$$

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