BARGAINING, THE VALUE OF UNEMPLOYMENT, AND THE BEHAVIOR OF AGGREGATE WAGES

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Abstract

In an environment where firms and workers bargain over the division of the surplus from the job-worker match, the resulting wage does not equal the marginal product. This paper explores the question whether such a model can advance our understanding of the behavior of aggregate wages. It does so by estimating a wage bargaining equation set within a model of the aggregate labor market with frictions. The equation posits that the wage is a function of current productivity, future productivity and the value of unemployment. We use Israeli aggregate labor market data, GMM and co-integration estimation methodologies, and allow for alternative specifications of endogenous bargaining power and of the value of unemployment.

Key results are that the role of the current marginal product is limited and the role of future productivity is small. Rather, workers’ value of unemployment plays an important part in the determination of wages in terms of both the mean and the variance. This value is determined by the value of home production and any non-pecuniary value, and, to a lesser extent, by net unemployment benefits.

Key words: value of unemployment, Nash bargaining solution, structural estimation, wage curve, unemployment benefits, wages and productivity.

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1 Introduction

This paper explores the question whether a bargaining model of wage determination – in the spirit of Diamond (1982a) and Mortensen (1982) – embedded in a framework of labor market frictions can advance our understanding of the determinants of aggregate wages and their behavior. In this model firms and workers bargain over the division of the match surplus and the resulting wage does not equal the worker’s marginal product. The interest in this exploration stems from a number of questions:

First, the empirical validity of the wage bargaining element of the Diamond-Mortensen-Pissarides search and matching model of the labor market has not been verified. This element in particular was criticized by Shimer (2003) as engendering difficulties for the model to fit U.S. labor market facts. More generally, while the model was shown to be useful in accounting for various macroeconomic phenomena [see, for example, Merz (1995), Mortensen and Pissarides (1999), and Yashiv (2000a)] a number of authors have pointed out that it does not match key facts [see, for example, Cole and Rogerson (1999) and Veracierto (2003)].

Second, the time series behavior of aggregate wages remains a challenging issue in macroeconomic research. Several difficulties have been noted: there is no evidence of systematically procyclical or countercyclical behavior of real wages, unlike some other macroeconomic regularities (see the survey provided in Abrahám and Haltiwanger (1995)); business cycle theories, particularly the standard RBC model, have difficulties in matching the moments of real wage behavior.2

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2 The standard model produces highly pro-cyclical real wage movements while U.S. data indicates weak procyclicality at best (see for examples Tables 1 and 3 in King and Rebelo (1999]). The RBC model with search and
Third, in a cross-sectional context, Blanchflower and Oswald’s (1994) study of the wage curve – the negative relation between real wages and regional unemployment – yields empirical inconsistencies with some of the major models of the aggregate labor market, including the neo-classical model.

The exploration of the model is undertaken through estimation of a wage equation derived from the Nash solution of the firm-worker bargaining problem. The model is a stochastic, discrete time version of the prototypical search and matching model. The equation posits that the wage is a function of current productivity, future productivity and the value of unemployment. The latter is a function of net unemployment benefits and the value of home production or production in the informal sector and any non-pecuniary value. The paper takes the model to aggregate Israeli labor market data. The reason for using this data set is that it has unique features that have already proved to be of significant value when coming to implement the model empirically [see Yashiv (2000a)]. Estimation generates two sets of results: one is the set of parameters defining the relative role of the determinants of wages − productivity (current and future) and the value of unemployment. The other is a set of time series of the components of wages, the bargaining strength of workers and firms, and the value of unemployment. We use the results to decompose wages and the value of unemployment, and to undertake a steady state simulation analysis. This analysis allows the study of the influence of key variables and parameters in the wage bargaining process on equilibrium unemployment, vacancies and wages. In particular this analysis generates well-defined Beveridge curves and ‘wage curves’. As the issue of market efficiency is closely related to the bargaining outcome, the empirical estimates also allow for the evaluation of market efficiency in a real-world aggregate labor market.

A key result is that the value of unemployment plays an important role in the determination of wages, in terms of both the mean and the variance. The role of current productivity, which is the only determinant of wages in the neo-classical model, is limited. This is so even though the matching, while improving the fit of wage behavior, has difficulties in matching other moments of the labor market [see Veracierto (2003)].
neo-classical case is nested in the empirical specifications. Other major findings are as follows: the estimated wage equation fits the data reasonably well. Workers’ bargaining power – allowed to be endogenous – does not vary much with market conditions. It is estimated to be around 0.1-0.3, in line with recent structural estimation using micro panel data. The value of unemployment is determined mostly by the value of home or informal production and any non-pecuniary value and, to a lesser extent, by net unemployment benefits. The simulation analysis of the model’s steady state demonstrates how the Beveridge curve (unemployment–vacancy relation) and wage curve (wages–unemployment relation) move when there is a change in key variables or in the parameters determining the wage bargain. Thus, for example, an increase in workers’ value of unemployment or in their bargaining power shifts the Beveridge curve towards less job creation and moves the wage curve towards a higher labor share of income coupled with higher unemployment. The results also suggest that workers’ share in the surplus division is “appropriate” from the standpoint of market efficiency.

The paper proceeds as follows: Section 2 presents the model. Section 3 presents the data and methodology. Section 4 delineates estimation results. The implications of the results with respect to the determinants of wages and of the value of unemployment are discussed in Section 5. Cyclical implications are discussed in Section 6. The steady state analysis of the Beveridge and wage curves is presented in Section 7. A brief discussion of the implications pertaining to market efficiency is given in Section 8. Section 9 concludes.

2 The Model

The main focus of this paper is on wage formation through bargaining over the division of the job-worker match surplus. Before describing the bargaining process it is necessary to formulate the search and matching context in which it takes place.
2.1 The Search and Matching Framework

The search and matching model of the labor market posits that there are two types of agents engaged in costly search: unemployed workers searching for jobs and firms searching for workers through vacancy creation. Matching is not instantaneous: workers and firms are faced with different frictions, such as different locations leading to regional mismatch, lags and asymmetries in the transmission of information and time-consuming processing of job applications. These frictions are embedded in the concept of a matching function at the aggregate level which produces hires out of vacancies and unemployment, leaving certain jobs unfilled and certain workers unemployed. Following matching the firm and the worker bargain over the division of the rents created by the match. The Nash solution is used to determine the outcome, with the wage being the part of the worker in this bargain. In this paper we look at the version of the model whereby all workers and all firms are homogenous and matches dissolve at a stochastic, exogenous rate. In what follows we briefly present the model; for a more extensive treatment see Mortensen and Pissarides (1999) and Pissarides (2000). The current presentation follows the stochastic, discrete-time formulation in Yashiv (2000a). The stochastic optimization framework to be presented accommodates random shocks to matching and to the variables affecting agents’ optimal behavior: labor productivity, unemployment benefits, taxes, the rate of separation, and the real rate of interest. The notation uses lower-case letters for micro-level variables and upper-case letters for aggregate ones.

2.1.1 Matching

The matching function acts like a production function, taking as inputs the stocks of unemployed workers and vacant jobs, producing a flow of hires.\(^3\) Formally:

\[
H_t = M(\theta_t, U_t, V_t)
\]

\(^3\)Petrongolo and Pissarides (2001) offer a survey of the literature on this topic.
where $H$ is the number of hires, $\theta$ is the level of the matching technology, $U$ is the number of unemployed (searching) workers, and $V$ is the number of job-vacancies. This function has positive first derivatives and should satisfy:

$$0 \leq H_t \leq \min(U_t, V_t)$$

Matching at the aggregate level implies that for homogenous firms there is a common probability $Q$ of filling a vacancy defined as follows:

$$q_t = Q_t = \frac{M(\theta_t, U_t, V_t)}{V_t}$$  \hspace{1cm} (2)

where $q, Q$ are the firm-level and aggregate vacancy matching probabilities, respectively.

Similarly with homogenous workers the matching probability for the unemployed worker is defined as follows:

$$p_t = P_t = \frac{M(\theta_t, U_t, V_t)}{U_t}$$  \hspace{1cm} (3)

### 2.1.2 Firms

The objective function of the firm is to maximize the sum of the present value of expected profits where its decision variable is vacancy creation. The firm’s problem may be examined with the tools of stochastic dynamic programming in the same way as has they have been used for capital investment problems, so the model is the analogue of “Tobin’s q” model of investment in physical capital. The timing is as follows: the firm makes its decisions on vacancy creation in period $t$ using the information set $\Omega_t$. Hired workers enter production in the following period ($t+1$). Separation of workers from jobs occurs at rate $s_t$. The stochastic dynamic programming problem is formulated as follows:

$$\max_{\{v\}} E_t \sum_{i=0}^{\infty} \frac{1}{\prod_{j=0}^{i}(1 + r_{t+j-1})} \left[ F(n_{t+i}, A_{t+i}) - w_{t+i} (1 + r_t^*) n_{t+i} - \Gamma(v_{t+i}, B_{t+i}) \right]$$  \hspace{1cm} (4)
subject to:

\[ n_{t+1} = n_t (1 - s_t) + q_t v_t \]  

where \( E_t \) denotes expectations formed in period \( t \) based on the information set \( \Omega_t \); \( F \) is the production function with employment \( (n) \) and other factors of production (contained in the vector \( A \)) as its arguments; real wage payments are denoted by \( w(1 + \tau_t^s)n \), where \( w \) are wages and \( \tau_t^s \) are employer taxes and contributions to social security (or any other overhead costs). We represent by \( \Gamma \) the costs of hiring which are of two types: (i) the cost of advertising, screening and selecting new workers and (ii) the cost of training. This function has as its arguments the number of vacancies \( (v) \) and possibly other variables (denoted by the vector \( B \); this vector could include the matching rate \( q \)). The firm uses the relevant interest rate \( r \) to discount future streams.

The F.O.C. (the so-called stochastic Euler equation) is:

\[
\frac{\partial \Gamma_t}{\partial v_t} = q_t E_t \frac{1}{1 + r_t} \left[ \frac{\partial F_{t+1}}{\partial n_{t+1}} - (1 + \tau_t^s)w_{t+1} - \frac{\partial \Gamma_{t+1}}{\partial n_{t+1}} + (1 - s_{t+1}) \frac{\partial \Gamma_{t+1}}{\partial v_{t+1}} \frac{\partial F_{t+1}}{\partial v_{t+1}} \right] 
\]  

(6)

The intuition here is that the marginal cost of hiring (the LHS) equals expected discounted marginal profits (the RHS). The latter depends on the rate at which vacancies get filled \( (q) \) and two terms expressing (i) the expected marginal profit at period \( t + 1 \), which is made up of the marginal product and the reduction in hiring costs due to the additional hire less the wage paid; and (ii) the expected savings of hiring costs if the worker does not separate in the following period.

2.1.3 Workers

When employed workers earn net wages \( w(1 - \tau) \), where \( \tau \) is the wage tax rate. During unemployment workers receive the net value of unemployment at time \( t \), to be denoted \( b_t \). We formulate it as consisting of unemployment benefits net of taxes \( z_t(1 - \tau_t) \), plus any other net value of unemployment, which we denote \( x_t \). The latter may consist of a non-pecuniary value, such as that derived
from leisure activities\textsuperscript{4}, home production or the value of production in non-formal sectors, and is net of search costs.

\begin{equation}
    b_t = z_t (1 - \tau_t) + x_t
\end{equation}

Evidently the value of $x_t$ is unobserved. In the empirical section below we elaborate on alternative formulations that try to capture it using proxy variables. In what follows we shall refer to $b_t$ as the (flow) value of unemployment.

Let $J^N_t$ be the present value of being employed and $J^U_t$ be the (stock or present) value of being unemployed. These are given by:

\begin{equation}
    J^U_t = b_t + \frac{1}{1 + r_t} E_t[p_t J^N_{t+1} + (1 - p_t) J^U_{t+1}] \tag{8}
\end{equation}

\begin{equation}
    J^N_{t+1} = w_{t+1} (1 - \tau_{t+1}) + \frac{1}{1 + r_{t+1}} [(1 - s_{t+1}) J^N_{t+2} + s_{t+1} J^U_{t+2}] \tag{9}
\end{equation}

The value of being unemployed $J^U_t$ is the sum of the flow value of unemployment this period $b_t$ and the expected value next period. This value is computed as the sum of two products: the product of the probability of being matched $p_t$ and the value of being employed $J^N_{t+1}$ and the product of the complementary probability $1 - p_t$ and the value of staying unemployed $J^U_{t+1}$. The value of being employed $J^N_{t+1}$ is the sum of the current net wage $w_{t+1} (1 - \tau_{t+1})$ and the expected value next period. The latter is the sum of two terms: the product of the probability to stay on the job $1 - s_{t+1}$ and the value of staying employed $J^N_{t+2}$ and the product of the probability of separation into unemployment $s_{t+1}$ and the value of being unemployed $J^U_{t+2}$.

\textsuperscript{4}Note that this value may be negative if, say, the value of leisure is dominated by the social and psychological costs of unemployment.
2.1.4 Equilibrium Outcome

The partial equilibrium outcome is obtained by solving equations (1), (5), (6), and the wage equation given below (equation 13), using the assumption of homogenous agents, for the stocks $U$ (or $N$) and $V$, the flow of hiring $H$, and the wage $w$. Consequently the matching rates $Q$ and $P$ are determined. This solution obtains given marginal productivity $\frac{\partial F_t}{\partial n_t}$, unemployment benefits $z_t$, wage taxes $\tau_t$, employer taxes and contributions $\tau^s_t$, the interest rate $r_t$, the separation rate $s_t$, the matching technology $\theta_t$ and the initial values of $U, N$ and $V$. For a fully worked out example of such a partial equilibrium set-up see Pissarides (1985). The model may also be embedded in a general equilibrium Merz (1995), for example, does so in the RBC framework where the exogenous driving shocks are technology shocks and hence the interest rate $r_t$ and marginal productivity $\frac{\partial F_t}{\partial n_t}$ are endogenized.

2.2 The Wage Solution

The wage solution, using generalized Nash bargaining, is given by:

$$w_t = \arg \max (J^N_t - J^U_t)^{\beta_t} (J^F_t - J^V_t)^{1-\beta_t}$$  \hspace{1cm} (10)

where $J^F_t - J^V_t$ is the firm’s net value of the match, $J^N_t - J^U_t$ is the worker’s net value of the match and $\beta_t$ is the time-varying parameter capturing workers’ bargaining power. The latter merits some discussion.

Binmore, Rubinstein and Wolinsky (1986) and Osborne and Rubinstein (1990) discuss the interpretation of this parameter in the context of mapping the Nash solution to a strategic bargaining model. This parameter may reflect differences in the bargaining environment which are not captured by the disagreement points, i.e. the outcome for the parties if bargaining does not result in an agreement. Thus, for example, it may capture the probability that workers make a wage demand in a given round of bargaining, or differences in impatience, with the value of $\beta_t$ determined by the disparity in the subjective discount factors of the firms and the workers. A specific idea in this context was proposed by Shaked and Sutton (1984). They considered sequential bargaining
between firms and workers, where the two sides alternate in making offers. In their analysis one party is free to switch between rival partners subject to a certain friction. We shall follow Shi and Wen (1999), who have applied the Shaked-Sutton model to the current context, and consider the case whereby the firm or the worker has the opportunity to switch to a new partner after $T$ rounds of negotiations. Nature chooses which party makes the offer in each round; the worker’s probability of making an offer shall be denoted by $\beta$. The number of bargaining rounds till the switch ($T$) is modeled as a function of the relevant market conditions. There are two polar cases of interest: in the first it is the firm that gets to switch. Shi and Wen (1999) show that in these circumstances the worker bargaining parameter is given by:

$$\beta_t = \frac{T_t \bar{\beta}^2}{1 - \beta + T_t \beta}$$

(11)

where $T_t = \frac{1}{q_t}$ since each vacancy is matched at rate $q_t$. In the second case it is the worker that gets to switch and thus:

$$\beta_t = \frac{\bar{\beta} + T_t \bar{\beta}(1 - \bar{\beta})}{\bar{\beta} + T_t (1 - \beta)}$$

(12)

where $T_t = \frac{1}{p_t}$. In reality it is likely that both worker and firm may get to switch so the true parameter is bound to be between the two polar cases. Thus the bargaining power parameter becomes a time-varying, endogenous variable. This formulation is consistent with the interpretation of $\beta_t$ as a type of summary statistic of the labor market position of workers [see the discussion in Flinn (2001)].

The solution of (10) yields:\textsuperscript{5}

$$w_t = \frac{\beta_t}{(1 + \tau_t^F)} \left[ \frac{\partial F_t}{\partial n_t} - \frac{\partial \Gamma_t}{\partial n_t} + E_t \frac{p_t}{1 + r_t} J_{t+1}^F \right] + \frac{(1 - \beta_t)}{(1 - \tau_t)} b_t$$

(13)

Note that when there are no search costs ($\frac{\partial \Gamma_t}{\partial n_t} = J_{t+1}^F = 0$) and no taxes ($\tau_t^F = r_t = 0$) the wage is just a weighted average of current productivity and the value of unemployment. Specifically \textsuperscript{5}The complete derivation is to be found in Appendix A.
when $\beta_t = 1$ we get the competitive solution i.e. $w_t = \frac{\partial F_t}{\partial n_t}$. Another way of interpreting equation (13) is the following. Suppose that there are no search costs i.e. $\gamma_1 = 0$ and no taxes i.e. $\tau_t = \tau_t^s = 0$ then:

$$\beta_t = \frac{w_t - b_t}{\alpha \frac{F_t}{N_t} - b_t}$$

Bargaining power $\beta_t$ reflects the ratio between the actual wage-value of unemployment premium $w_t - b_t$ and the productivity-value of unemployment premium $\alpha \frac{F_t}{N_t} - b_t$.

In what follows we shall discuss the wage in terms of its share in average output $\frac{w}{N}$ or, in other words, in terms of the labor share of income $\frac{wN}{F}$. This is also equivalent to real unit labor costs.

The match surplus is given by:

$$S_t = J_t^F + J_t^N - J_t^U$$  \hspace{1cm} (14)

The worker’s share of the rent is therefore defined as follows:

$$\frac{J_t^N - J_t^U}{S_t} = \frac{(1 - \tau_t)}{(1 - \tau_t \beta_t) + \tau_s \tau_t (1 - \beta_t)} \beta_t$$  \hspace{1cm} (15)

Note that with taxes the worker’s share differs from $\beta_t$.

When implementing the model empirically we need to take into account that observed real wages may differ from desired ones due to errors in inflationary expectations. We follow Card (1990) in postulating the following, using a tilde above a variable to denote actual or observed value. Actual log real wages are given by:

$$\ln \tilde{w}_t = \ln \tilde{W}_t - \ln \tilde{P}_t$$  \hspace{1cm} (16)

The desired log real wage in this framework is given by:

$$\ln w_t = \ln B_t$$  \hspace{1cm} (17)
where

\[ \dot{B}_t = \frac{\beta_t}{(1 + \tau_t)} \left[ \frac{\partial F_t}{\partial n_t} - \frac{\partial \Gamma_t}{\partial n_t} + E_t \frac{p_t}{1 + r_t} J_t^{F+1} \right] + \frac{(1 - \beta_t)}{(1 - \tau_t)} b_t \]

Actual and desired real wages may differ because of differences in expected and actual price levels:

\[ \ln \tilde{w}_t - \ln w_t = -(1 - e)(\ln \tilde{P}_t - \ln P^e_t) \quad (18) \]

where \(0 \leq e \leq 1\) is the rate of indexation and \(P^e\) are expected prices. When \(\tilde{P}_t > P^e_t\) and when indexation is not full \((e < 1)\) actual wages are lower than desired wages, i.e. \(\tilde{w}_t < w_t\).

Inserting the value of desired (log) wages \(\ln w_t\) from (17) we get:

\[ \ln \tilde{w}_t = \ln B_t - (1 - e)(\ln \tilde{P}_t - \ln P^e_t) \quad (19) \]

It follows that:

\[ \ln \tilde{w}_t = \ln B_t - (1 - e) \left[ (\ln \tilde{P}_t - \ln \tilde{P}_{t-1}) - (\ln P^e_t - \ln \tilde{P}_{t-1}) \right] \quad (20) \]

Postulating rational expectations, i.e.:

\[ (\ln P^e_t - \ln \tilde{P}_{t-1}) = (\ln \tilde{P}_t - \ln \tilde{P}_{t-1}) + \xi_t \quad (21) \]

Therefore:

\[ \ln \tilde{w}_t = \ln B_t + (1 - e)\xi_t \quad (22) \]

Hence the error term emerges from errors in rationally-expected inflation with incomplete real wage indexation.
3 Data and Methodology

3.1 The Data

We use aggregate Israeli labor market data to estimate the model. This data-set was chosen because it is of unique quality: it is Employment Service (ES) data on unemployment, vacancies and matches which offer a wide coverage of the market and contain measures of both sides of the search process (unemployed workers and firms’ vacant jobs) consistent with the theoretical model and well-defined. Moreover, structural estimates in Yashiv (2000a) indicate that the model - data fit is reasonably good. We briefly describe the institutional set-up of this market and then present the data series. The latter also include data on real output, wages, and unemployment benefits.

3.1.1 The Israeli Labor Market

This market is essentially composed of two main segments: the market for jobs that do not require a university degree and the market for jobs that require academic qualifications. Matching of workers and jobs in the former segment is done by the main institutional intermediary in the Israeli labor market, the Employment Service, which is affiliated to the Ministry of Labor. From 1959 until March 1991 private intermediaries were illegal and hiring of workers for these jobs was required by law to pass through the ES. On the other side of the market, unemployed workers must register with the ES in order to qualify for unemployment benefits. Firms post vacancies in quite specific terms: they are required to fill out a detailed form when registering vacancies including their exact number and the type of job required, and have to renew them at the beginning of each month. This procedure renders vacancies a concrete meaning and places them on equal footing with the unemployment figures. The latter are the result of workers’ appearances at the ES bureau where they too filled out a detailed form. Therefore ES data give comprehensive coverage and offer the opportunity to study unemployment, vacancies and matches that are well defined. There are several indications with respect to the relative size of the ES segment: the share of university graduates among employed workers was 35 percent at the end of the sample period and lower than
that – at around 20-25 percent – in the course of the period. The ratio of ES unemployment to unemployment according to the Labor Force Survey (LFS) was about 60 percent on average in the years 1962 (when ES measurement began) till 1989 (the end of the period of vacancy availability). Therefore a lower bound on the share of the ES segment is 60 percent of the market and it would not be unreasonable to estimate its actual share in the sample period as 70-80 percent.

3.1.2 Data Series

Unemployment, vacancies and matches data are taken from the administrative records of the ES. Wage and unemployment benefits data are taken from the National Insurance Agency (NIA). Other data used are business sector NIPA and LFS data from the Central Bureau of Statistics (CBS). Appendix B provides full definitions and a list of sources.

ES data generate the $U, V$ and $H$ series described above. We take business sector employment ($N$) from the LFS. The matching probabilities ($Q$ and $P$) and the labor force ($L$) are derived from these series.

Wages ($w$), unemployment benefits ($z$) and average output ($F$) are standard business sector data (see Appendix B for exact definitions). High frequency time series on taxes – workers’ wage and unemployment benefits taxes ($\tau$) and employers’ taxes and contributions ($\tau^s$) – are unavailable. We use the assumption that they are constant throughout the year.

Given data availability constraints, in the empirical work we deal with two data samples: First, a restricted sample 1976:01-1989:12 (n=168) which contains all series. Then, some runs are performed on a longer sample – 1976:01-2001:12 (n=312) – which has no data on vacancies and hiring. Table 1 presents data summary statistics and Figure 1 plots two key series – the labor share or unit labor costs and the replacement ratio.

**Table 1 and Figure 1**

The labor share of income including employer contributions ($\frac{wN(1+\tau^s)}{F}$) averaged 60% during
the sample period. This figure is comparable to the OECD average; for example Bentolila and Saint Paul (2001) report an average of 68.8% in 1980 and 65.5% in 1990 for 14 OECD economies.

3.2 Methodology

In this sub-section we present estimation issues that need to be resolved, parameterization of the functional forms, alternative specifications of the bargaining parameter, the estimating equations, and the econometric methodology.

3.2.1 Estimation Issues

There are a number of essential issues that need to be dealt with:

a. The formulation of the bargaining power. If an endogenous bargaining power parameter is to be allowed, its functional form and the variables determining it need to be specified.

b. The part of the bargain capturing future match productivity is based on the firms’ hiring costs. This requires the formulation of both the production function \( F \) and the firm’s hiring cost function \( \Gamma \) and estimation of the relevant Euler equation.

c. The workers’ value of unemployment contains net unemployment benefits and an unobserved component. The latter needs to be proxied using available data and requires a specification for functional form.

d. Each econometric methodology requires certain conditions: when we use GMM we need to induce stationarity and to choose instrumental variables; when we use co-integration, unit root tests need to be applied.

We turn now to a detailed discussion of these issues.

\(^6\)Without employer contributions (\( w_N \)) the share averaged 54% in the sample period. The difference, due to \( \tau \), is comparable to that reported by Krueger (1999) for the U.S.
3.2.2 Functional Forms

In order to implement the model empirically, it is required to parameterize the production function \( F \) and the firm’s hiring cost function \( \Gamma \).

For the production function \( (F) \) we take a “traditional” route and specify a Cobb-Douglas function; this enables us to use the average product, which is proportional to the marginal product, in estimation:

\[
F_t = A_t n_t^\alpha k_t^{1-\alpha} \tag{23}
\]

For the hiring cost function \( (\Gamma) \), first consider the arguments of the function. We refer here to gross hiring costs as distinct from net costs. By gross costs we refer to both the costs of screening (interviewing, testing, etc.) and the costs of training. The former relate to all vacancies; the latter only to actual hires. In order to take into account the size of the firm, we model these costs as a function of hiring rates out of the economy-wide labor force and as proportional to output, i.e. \( \Gamma = \tilde{\Gamma}(\frac{v_t}{L_t}, \frac{q_t}{v_t})F_t \), where \( \tilde{\Gamma} \) is some increasing function and \( L_t = N_t + U_t \). The function is linearly homogenous in \( v, L, k \) and \( n \), and costs are internal to the production process. Estimation results in Yashiv (2000a,b) show that for the functional form of hiring costs (the shape of \( \tilde{\Gamma} \)) a general, unconstrained power works best. Thus we use:

\[
\Gamma_t = \frac{\gamma_1}{\gamma_2} (\psi \frac{v_t}{L_t} + (1 - \psi) \frac{q_t v_t}{L_t})^{\gamma_2} F_t \tag{24}
\]

The parameter \( \gamma_2 \) captures the elasticity of the hiring function w.r.t. its determinants, \( \gamma_1 \) is a scale parameter and \( \psi \) is the fraction of costs that fall on screening. Note that in the special case \( \psi = \gamma_2 = 1 \) the linear specification obtains.

Below we make use of the following derivatives of this function:

\[
\frac{\partial \Gamma_t}{\partial v_t} = \gamma_1 \left( \psi \frac{v_t}{L_t} + (1 - \psi) \frac{q_t v_t}{L_t} \right)^{\gamma_2-1} (\psi + (1 - \psi) q_t) \frac{F_t}{L_t} \tag{25}
\]
\[
\frac{\partial \Gamma_t}{\partial n_t} = \frac{\gamma_1}{\gamma_2} (\psi \frac{v_t}{L_t} + (1 - \psi) \frac{q_t v_t}{L_t})^{\gamma_2} \frac{\partial F_t}{\partial N_t}
\] (26)

Note that these derivatives are predicated on the set-up whereby the firm takes \(q\) and \(L\) as given.

### 3.2.3 Wage Bargaining

The discussion in section 2.2 implied two possibilities for modelling the bargaining power parameter \(\beta_t\): (i) a fixed parameter \(\beta_t = \bar{\beta}\); (ii) a time-varying parameter dependent on market conditions.

For the latter four alternative formulations are used: two are given by equation (11) i.e. \(\beta_t = \frac{T_t \bar{\beta}^2}{1 - \beta T_t}\) where \(T_t = \frac{1}{q_t}\) and equation (12) i.e. \(\beta_t = \frac{\bar{\beta} + T_t \bar{\beta} (1 - \beta)}{\beta + T_t (1 - \beta)}\) where \(T_t = \frac{1}{p_t}\). The other two are functions of market tightness \(v_u\) and use two prevalent functional forms – linear and logistic:7

\[
\beta_t = \bar{\beta} \left( \frac{v_t}{u_t} \right)
\] (27)

\[
\beta_t = \frac{\exp \bar{\beta} \left( \frac{v_t}{u_t} \right)}{1 + \exp \bar{\beta} \left( \frac{v_t}{u_t} \right)}
\] (28)

The rationale behind these formulations is to try a functional form less specific than the Shi-Wen formulation.

### 3.2.4 The Value of Unemployment

It was indicated above that the value of unemployment is given by:

\[
b_t = z_t (1 - \tau_t) + x_t
\] (29)

For the unobserved \(x_t\) we try a number of formulations:

---

7Note that under a constant returns to scale matching function \(q\) and \(p\) used in the first two formulations are also functions of \(\bar{\varepsilon}\).
a. The unobserved component is proportional to productivity \( \frac{F_t}{N_t} \). We thus postulate a linear formulation:

\[
x_t = \mu \frac{F_t}{N_t}
\]

b. The unobserved component is proportional to productivity \( \frac{F_t}{N_t} \) and depends on the labor force participation rate \( \frac{F_t}{POP_t} \), where \( L \) is the labor force and \( POP \) is working-age population:

\[
x_t \frac{F_t}{N_t} = \mu_1 \frac{L_t}{POP_t} + \mu_2 \left( \frac{L_t}{POP_t} \right)^2
\]

The participation rate may affect \( \frac{x_t}{N_t} \) in two ways: it may indicate willingness to participate in production in general, including home production or production in the informal sector. In this case it will have a positive effect on \( \frac{x_t}{N_t} \). It may also indicate a move from home or informal production to formal market production. In this case it will have a negative effect on \( \frac{x_t}{N_t} \).

Alternatively we try a formulation which makes \( \frac{x_t}{N_t} \) a function of the male and female participation rates:

\[
x_t \frac{F_t}{N_t} = \mu_1 \left( \frac{L_t}{POP_t} \right)^{male} + \mu_2 \left( \frac{L_t}{POP_t} \right)^{female}
\]

c. We also examine a reference case of \( x_t = 0 \) i.e. the value of unemployment consists only of benefit payments.

### 3.2.5 Estimating Equations

The equation which is at the heart of the analysis is equation (13) i.e.:

\[
w_t = \beta_t \left[ \frac{\partial F_t}{\partial n_t} - \frac{\partial \Gamma_t}{\partial n_t} + E_t \frac{p_t}{1 + r_t} J_{F_t+1} \right] + \frac{(1 - \beta_t)}{(1 - \tau_t)} b_t
\]

At the aggregate level this equation may be re-written as follows, dividing throughout by \( \frac{F_t}{N_t} \) to induce stationarity and inserting equations (7), (23), (26), as well as (35) (given in Appendix A):
\[
\frac{w_t}{F_t} = \frac{\beta_t}{(1 + \tau_t)} \left( \alpha \left( 1 - \left[ \frac{\gamma_1}{\gamma_2} \left( \psi \frac{V_t}{L_t} + (1 - \psi) \frac{Q_t V_t}{L_t} \right)^{\gamma_2} \right] \right) + \frac{V_t}{F_t} \gamma_1 \left( \psi \frac{V_t}{L_t} + (1 - \psi) \frac{Q_t V_t}{L_t} \right)^{\gamma_2-1} (\psi + (1 - \psi) Q_t) \frac{N_t}{L_t} \right) \\
+ \frac{(1 - \beta_t)}{(1 - \tau_t)} \left[ \frac{z_t (1 - \rho_t)}{F_t} + \frac{x_t}{F_t} \right]
\]

Note that the parameters \(\alpha, \gamma_1, \gamma_2, \psi\) come from the firms' F.O.C (6) which may be written as follows:

\[
\gamma_1 \left( \psi \frac{V_t}{L_t} + (1 - \psi) \frac{Q_t V_t}{L_t} \right)^{\gamma_2-1} (\psi + (1 - \psi) Q_t) \frac{F_t}{L_t} \\
= Q_t \frac{1}{1 + \tau_t} \frac{F_t + 1}{N_t} \frac{F_t}{F_t} \left[ \alpha \left( 1 - \left[ \frac{\gamma_1}{\gamma_2} \left( \psi \frac{V_t + 1}{L_t + 1} + (1 - \psi) \frac{Q_t V_t + 1}{L_t + 1} \right)^{\gamma_2} \right] \right) - \frac{(1 + \tau_t) N_t + 1}{F_t + 1} \\
+ (1 - \rho_t) \gamma_1 \left( \psi \frac{V_t + 1}{L_t + 1} + (1 - \psi) \frac{Q_t V_t + 1}{L_t + 1} \right)^{\gamma_2-1} (\psi \frac{1}{Q_t + 1} + (1 - \psi)) \frac{N_t + 1}{L_t + 1} \right]
\]

### 3.2.6 Estimation Methodology

We undertake two sets of estimation procedures: in the first we estimate (30) and (31) using GMM in the sample period where all data series are available – 1976:01-1989:12. The results indicate that a fixed \(\beta\) is a reasonable approximation and that the future productivity part of the bargain is small. This allows us to utilize the information from the longer sample period – 1976:01-2001:12. Thus, in a second procedure we drop the endogenous \(\beta\) formulations as well as the future productivity part of the bargain, both depending on vacancy data which are unavailable in the longer sample. We estimate this simplified equation using both GMM and the Engle and Granger (1987) co-integration methodology.

When applying Hansen’s (1982) GMM methodology, the estimated wage equation is:

\[
\ln \tilde{w}_t = \ln B_t + (1 - e) \xi_t
\]

We rely on the orthogonality restrictions implied by rational expectations i.e. that the errors are orthogonal to any variable in the information set at time \(t\):
\[ E(\xi_t \otimes Z_t) = 0 \]

with \( Z \) a vector of instrumental variables. We use monetary variables, such as the growth rate of M1 or the nominal rate of interest, which are relevant for inflationary expectations, and the variables that appear in the equation itself. The GMM procedure allows us to estimate the \( \beta \) formulations, some of which are non-linear.

In the co-integration case the simplified wage equation in its non-stationary form using OLS is given by:

\[
 w_t = \frac{\beta_t \alpha}{(1 + \tau_t^s) N_t} F_t + \frac{(1 - \beta_t)}{(1 - \tau_t)} b_t
\]

4 Estimation Results

Table 2 presents the results of GMM estimation of the full specification of the wage equation (30) in the sample period 1976-1989.

We first present (in panel I) the results of estimation of the firms’ F.O.C (equation 31). This is needed in order to set the values of \( \alpha \) (the production function parameter) and \( \gamma_1, \gamma_2 \) and \( \psi \) (the hiring costs function parameters) in the wage equation. The estimates are close to those obtained using a similar specification in Yashiv (2000a,b). As discussed in these papers they imply a reasonable value of marginal hiring costs \( (\frac{\partial \Gamma_t}{\partial v_t}) \), equivalent to a week to two weeks worth of wages. The production function parameter \( \alpha \) is estimated at the reasonable value of 0.62. The parameter which exhibits some variation across specifications and a sizeable standard error is the scale parameter \( \gamma_1 \). In order to reflect this variation, in estimation below we set two alternative values (200,000 or 400,000).

---

\[ ^8 \text{Given the numerous specifications explored in Yashiv(2000a,b) we present only two “representative” specifications here. The difference between the two is the fixing or the estimation of } \psi. \]
In panel II we report the results for the wage equation. We begin by looking at the alternative specifications of $\frac{x_t}{FT}$ (which is part of the value of unemployment $\frac{b_t}{FT}$) discussed above. This is reported in sub-panel a. The table reports the point estimates and standard errors of the estimated parameters $\beta, \mu_1$ and $\mu_2$; the mean and standard deviation of the implied sample value of $\frac{x_t}{FT}$ computed using the point estimates; and two test statistics: the value and p-value of Hansen’s J-statistic [see Hansen (1982)] and the correlation between the fitted and actual $\frac{wN}{F}$.

Table 2

Columns 1a-3b of panel IIa convey the following picture: the bargaining parameter $\beta$ is imprecisely estimated; it is slightly negative in 1a and 1b and is around 0.10 in the other columns. The sample mean of $\frac{x_t}{FT}$ is around 0.31 with a small standard deviation. The fit of the equation — in terms of correlation between actual and fitted $\frac{wN}{F}$ is 0.7. We experiment — in column 4 — with a specification that drops the $\frac{x_t}{FT}$ term. The equation’s performance becomes very poor: the p-value indicates very strong rejection and the correlation between actual and fitted $\frac{wN}{F}$ is negative. The conclusions one can draw thus far are as follows: the $\frac{x_t}{FT}$ term is crucial for the equation’s performance and is very stable across specifications, but if set to be a constant it yields an implausible value of $\beta$. Using the other, time-varying specifications, one obtains a $\frac{x_t}{FT}$ series that has the same average and produces reasonable $\beta$ estimates.

Panel IIb goes on to examine the alternative formulations of $\beta$ discussed above, using the $b_t$ specification of column 3a in panel IIa. The logistic specification of $\beta$ did not converge. The Shi-Wen formulations are reported as well as the fixed and linear $\beta$. The mean and standard deviation of the implied $\beta_t$ using the point estimates of $\tilde{\beta}$ are reported as well as the parameter estimates. It turns out that these endogenous formulations do not matter much, with $\beta_t$ remaining around 0.07-0.10 on average.

Panel IIc picks up the specification of column 3a from panel IIa and uses alternative instrument sets. The results indicate robustness.
For the reasons elaborated above, we move on to estimation of a simplified wage equation setting $\gamma_1 = 0$. Table 3 shows the estimation results using the longer sample period 1976-2001 and both GMM and co-integration methodologies.

Table 3

The table begins with unit root tests of the relevant variables. Panel (a) shows that these variables are all I(1). Panel (b) presents the estimates using a fixed $\beta$ and the alternative specifications of $\frac{\bar{w}}{\bar{f}}$ discussed above. In order to facilitate comparison with the preceding results, column 1 takes up the specification used in column 3a of panel (a) in Table 2II and runs it again in the shorter period 1976-1989. The table indicates no change with respect to the mean value of the implied $\frac{\bar{w}}{\bar{f}}$ and an increase in the point estimates of $\beta$ to around 0.2. Throughout, the value of the residuals’ ADF statistic indicates rejection of a unit root, the $R^2$ is around 0.8 and the correlation between fitted and actual $\frac{wN}{F}$ remains around 0.7.

The last panel (II) shows the estimates of this sample period and specification using GMM. Here the point estimates of $\beta$ are slightly higher ranging between 0.25 and 0.32 and the same mean value of the implied $\frac{\bar{w}}{\bar{f}}$. Here too the correlation between fitted and actual $\frac{wN}{F}$ is around 0.7.

Summing up the results of the two tables the following conclusions emerge:

(i) The value of unemployment $\frac{\bar{w}}{\bar{f}}$ is stable at around 0.30 across specifications and plays an important role.

(ii) The value of bargaining power does not vary much when allowed to be endogenous.

(iii) Bargaining power is around 0.1-0.3 across the different formulations of the equation, sample periods, specifications of the $x_t$ part of the value of unemployment, and econometric methodologies. This implies that a key role in wage formation is played by the value of unemployment.

How reasonable are these estimates? With respect to the bargaining parameter, there are few micro studies, with researchers often assuming a value of 0.5. Two exceptions are the following: Flinn (2001) uses U.S. CPS data on young workers and structural estimation. His major estimates
are in the range of 0.42 to 0.50 for certain specifications, with relatively low standard errors, and 0.07 to 0.29 for other specifications, typically with large standard errors. Cahuc, Postel-Vinay and Robin (2002) use a French panel of matched employer-employee data to estimate this parameter, finding it to be 0 for unskilled workers in most industries and on average 0.30 for skilled workers. The results here are consistent with these findings, particularly the latter study.

To judge the plausibility of the estimates of $\frac{x}{N}$, there are a number of studies to consider:

(i) Two recent micro studies structurally estimated a search model with bargaining using U.S. data: Eckstein and Wolpin (1995), using NLSY data, report reservation wages defined as $rJ^U$ at the steady state (see their Table 5, p.282). In the current model this is given by:

$$rJ^U = \frac{(1 + r)(r + s)}{r + s + p} [b + \frac{pw(1 - \tau_t)}{r + s}]$$

If we divide the predicted mean $rJ^U$ by the mean of actual wages (i.e. $\frac{rJ^U}{w}$) their estimates range between 49% and 65%. The afore-cited study by Flinn (2001), using CPS data, reports values in a similar range – 49% to 60% (based on his Tables 1 and 2a). Inserting the sample mean values of $r, s, p, w$ and the implied estimate of $b$ from Tables 2 and 3 we get 86%. Thus the estimated $b$ here generates a value of $rJ^U$ somewhat higher than the upper bound of the afore-cited studies.

(ii) A range of estimates of the value of aggregate home production in the U.S. is presented in Eisner (1988). The estimates are mostly between 30% and 50% of output (net of home production). Here the estimate of $x$ which captures this value, less any search costs and disutility of unemployment, has a sample mean of around 30% of average output per worker. Thus this estimate too is reasonable.

To further see the implications of the results, we select two specifications – column 3a of Table 2IIa and column 3 of Table 3Ib – and study them using various decompositions.
5 Wage Decompositions

In this section we decompose the wage bargain in terms of average output (or, put differently, real unit labor costs) \( \frac{w}{F/N} \) into its components. The wage bargain \( \frac{w}{F/N} \) is essentially made up of three terms:

(i) **Current productivity**, captured by the term \( \alpha \left( 1 - \left[ \frac{\gamma_1}{2} \left( \psi \frac{\alpha}{L_t} + (1 - \psi) \frac{\alpha}{L_t} \right) \right]^2 \right)^9 \). This is multiplied by the appropriate worker share i.e. \( \frac{\beta_t}{(1 + \tau_t)} \) which is the worker’s bargaining strength \( \beta_t \) corrected for employer taxes and contributions \( \tau_t \). Note that the competitive case \( w = \frac{\beta_t}{(1 + \tau_t)} \) obtains as a special case i.e. when there are no search costs \( (\gamma_1 = 0) \), no employer contributions \( (\tau_t = 0) \) and the workers’ bargaining power is full \( (\beta_t = 1) \).

(ii) **Future productivity**, captured by the term \( FV_t \) multiplied by the same worker share \( \frac{\beta_t}{(1 + \tau_t)} \). The term \( FV_t \) includes the expected discounted future value of the match \( J_{t+1} \) multiplied by the worker’s matching probability \( P_t \).

(iii) **The value of unemployment** \( b_t \) multiplied by \( \frac{\beta_t}{(1 + \tau_t)} \). This factor is the complement of the worker’s bargaining strength \( 1 - \beta_t \) corrected for wage taxes \( \tau_t \). If workers had no bargaining power \( (\beta = 0) \) then the wage would be set to the value of unemployment, i.e. \( w_t (1 - \tau_t) = b_t \).

Table 4 reports three sets of statistics: panel a reports the value of the bargaining parameter \( \beta \) and the workers’ share in the match surplus \( \frac{J_t - J_{t+1}}{s_t} \). Panel b reports the mean fitted \( \frac{w_t}{N_t} \) and its decomposition into the above components according to the selected estimates of Tables 2 and 3. Panel c reports the variance-covariance matrix of these components, with each entry indicating the fraction with respect to the variance of \( \frac{w_t}{N_t} \).

Table 4

Three basic points emerge from Table 4:

---

9 The discussion here is set in terms of values relative to \( \frac{F}{N} \) i.e. \( \frac{\beta_t}{(1 + \tau_t)} \). The expression is made up of the production function parameter \( \alpha \) and an expression that takes into account the change in hiring costs due to a change in \( n \).
(i) The workers’ share in the match surplus \( \frac{J^U - J^U_{t,t}}{8_t} \), taking taxes into account, is somewhat lower than bargaining power.

(ii) In terms of the mean, as reported in Panel b of Table 4, the picture that emerges across specifications is that the big part – more than 50% – is played by the \( \frac{F_t}{N_t} \) term, unemployment benefits account for almost a third, the role of future productivity is negligible, and current productivity has a small part.

(iii) In terms of variance, as can be seen in panel c of Table 4, net unemployment benefits play a key role. Some role is played by the \( \frac{F_t}{N_t} \) part.

Combining these three points implies that the relatively low share of workers in the bargain gives a dominant role to the value of unemployment \( b_t \) in wage determination. Within this value, \( \frac{F_t}{N_t} \) is dominant in determination of the mean, while net unemployment benefits are dominant in determination of the variance.

6 Cyclical Properties

Given the difficulties encountered in macroeconomic research in accounting for the cyclical behavior of wages cited above, it is of interest to look at the cyclical properties of wages and their determinants. Table 5 documents in two panels these properties. We look at two cyclical indicators – real business sector GDP \((F)\) and business sector employment \((N)\) using two alternative detrending methods: log-linear (denoted by a \( LOG \) superscript) and HP filter of the log (denoted by a \( HP \) superscript).

Table 5

<table>
<thead>
<tr>
<th>Panel</th>
<th>Detrending Methodology</th>
<th>Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel (a)</td>
<td>HP filtered and log-linear</td>
<td>0.58</td>
</tr>
<tr>
<td>Panel (b)</td>
<td>HP filtered and log-linear</td>
<td>0.33</td>
</tr>
</tbody>
</table>

First, panel (a) shows that the detrending methodology matters: the correlation between HP filtered and log-linear detrended business sector GDP is just 0.58 and for business sector employment it is even lower (0.33). A similar phenomenon is reported for U.S. data in Abraham and Haltiwanger (1995).
Panel (b) shows that when measuring the cycle using business sector GDP, wages – either detrended wages or the labor share – are counter-cyclical, albeit sometimes very weakly. When measuring the cycle using business sector employment, much depends on the detrending method: with the HP-filtered measure the relationship is weakly pro-cyclical; with log-linearly detrended employment it is moderately counter-cyclical.

Looking at the determinants of wages we find the following: the first term $\frac{\beta \alpha}{1+\tau_s}$ which fluctuates because of taxes $\tau_s$ is weakly to moderately pro-cyclical; the other terms and their constituents – unemployment benefits $\frac{x}{F/N}$ and the term $\frac{x}{F/N}$ – are generally counter-cyclical.

From this somewhat inconsistent picture what does emerge is the following:

a. When coming to establish business cycle properties much depends on the cyclical measure and the detrending methodology.

b. Basically the wage appears to be moderately or weakly counter-cyclical.

c. The main components of the wage bargain as estimated above – unemployment benefits $\frac{x}{F/N}$ and the term $\frac{x}{F/N}$ – generate the counter-cyclicality of wages.

7 Steady State Analysis: Beveridge Curves and Wage Curves

The results can provide lessons with respect to the behavior of some well-known relations – the relation between unemployment and vacancies, known as the ‘Beveridge curve’, and the relation between wages and unemployment, known as the ‘wage curve.’ We derive these curves as follows: we formulate the non-stochastic steady state of the model. The two curves are obtained by deriving the model’s solution under different values of the exogenous variables. We then examine how the curves move when key parameters change. In particular we look at the effects of changing bargaining power ($\beta$) and the value of unemployment ($b$).
7.1 The Steady State

We write the wage equation (30) and the firms’ Euler equation (31) in their steady state form as follows:

\[
\frac{w}{F/N} = \frac{\beta}{(1+\tau_0)} \left( \gamma_1 \left( \psi \frac{V}{L} + (1-\psi) \frac{QV}{L} \right)^{\gamma_2} \right) - (1-\beta) \frac{b}{(1-\tau) \frac{F}{N}} + (1-\beta) \left( 1 - \frac{2}{\gamma_2} \left( \psi \frac{N}{L} + (1-\psi) \frac{Q}{L} \right) \right) \]

\[+ \frac{1+\tau_0}{\gamma_2} \left( \psi \frac{V}{L} + (1-\psi) \frac{QV}{L} \right)^{\gamma_2-1} \left( \psi + (1-\psi) \frac{Q}{L} \right) \frac{N}{L} \]

\[= \frac{Q}{r+s-g^f(1-s)} \left[ \alpha \left( 1 - \frac{\gamma_1}{\gamma_2} \left( \psi \frac{V}{L} + (1-\psi) \frac{QV}{L} \right) \right) - \frac{(1+\tau_0)w}{F/N} \right] \]

where \( g^f \) is the rate of growth of labor productivity \( \frac{F}{N} \).

We add a steady state flow equation whereby the flow into unemployment equals the flow out of it, using a Cobb-Douglas matching function:

\[
\theta U^\xi V^{1-\xi} = sN \tag{34}
\]

where \( \theta \) is the matching technology parameter and \( \xi \) is the elasticity parameter.

This system of three equations is to be solved numerically for the three endogenous variables \( U, V, \) and \( w \). Their solution determines \( N, Q, \) and \( P \). The system is solved given the exogenous variables \( \frac{F}{N}, g^f, L, r, z, \tau, \tau_0 \) and \( s \). We also use a fixed and exogenous \( \beta \).

7.2 Baseline Values

In order to solve the model we use the following baseline values. We express labor force variables \( (U, N, V) \) in terms of rates out of the labor force (i.e. divide by \( L \)) and output variables \( (w, z) \) in
terms of output per worker (i.e. divide by \( \frac{F}{N} \)). We set the variables at their sample average value using the longest sample available. The resulting values (in monthly terms) are thus given by:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Steady State Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g^f )</td>
<td>0.001</td>
</tr>
<tr>
<td>( r )</td>
<td>0.01</td>
</tr>
<tr>
<td>( z )</td>
<td>0.18</td>
</tr>
<tr>
<td>( \tau )</td>
<td>0.11</td>
</tr>
<tr>
<td>( \tau^s )</td>
<td>0.16</td>
</tr>
<tr>
<td>( s )</td>
<td>0.024</td>
</tr>
</tbody>
</table>

For the parameters we use the point estimates from Table 3b column 3 and from Yashiv (2000a,b):

<table>
<thead>
<tr>
<th>Parameter Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>( \beta )</td>
</tr>
<tr>
<td>( x )</td>
</tr>
<tr>
<td>( \gamma_1 )</td>
</tr>
<tr>
<td>( \gamma_2 )</td>
</tr>
<tr>
<td>( \psi )</td>
</tr>
<tr>
<td>( \alpha )</td>
</tr>
<tr>
<td>( \xi )</td>
</tr>
<tr>
<td>( \theta )</td>
</tr>
</tbody>
</table>

Two parameters did not appear in the empirical section above: \( \xi \), the matching function elasticity parameter, was structurally estimated in Yashiv (2000a) to be about 0.3. The matching
function scale parameter $\theta$ is calibrated so that the model will produce a steady state solution for $\frac{U}{L}$ that will match its data average of 7.5%.

The solution of this baseline is the following:

<table>
<thead>
<tr>
<th>variable</th>
<th>solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{U}{L}$</td>
<td>7.5%</td>
</tr>
<tr>
<td>$\frac{V}{L}$</td>
<td>1.8%</td>
</tr>
<tr>
<td>$\frac{w}{N}$</td>
<td>0.54</td>
</tr>
</tbody>
</table>

7.3 Steady State Curves

The above system has produced a solution consisting of one steady state value for each variable $\frac{U}{L}$, $\frac{V}{L}$, and $\frac{w}{N}$. If we now vary one of two exogenous variables – productivity growth $g^f$ or the real rate of interest $r$ – within a reasonable range we get a steady state curve in $\frac{U}{L} - \frac{V}{L}$ and in $\frac{U}{L} - \frac{w}{N}$ space as shown in the four panels of Figure 2. The origin in each plot is the steady state point described above.

Figure 2

The mechanism underlying the curves is the following: when the interest rate rises or productivity growth declines the firm’s present value of the match declines. Hence vacancy creation declines. This leads to lower matching and higher unemployment. As the value of the match declines so do wages. Hence vacancies and wages go down as unemployment rises. Note that this mechanism provides a foundation for the downward sloping wage curve. This feature of the wage curve is inconsistent with some models of the labor market, including the traditional textbook model [see the discussion in Blanchflower and Oswald (1994)].

We now generate families of Beveridge and wage curves. Each curve is generated by varying the real rate of interest and is plotted in different color in the figures. Each family of curves is
generated by varying one parameter. Note that each curve’s length is determined by the variation in the rate of interest, as shown in Figure 2 above.

Figure 3

Figure 3 shows the effects of changing the bargaining outcome. Increasing the workers’ share of the bargain – via an increase in $\beta$ or $b$ (via $z$ or $x$) – increases wages and erodes firms’ profits. This leads to lower vacancy rates and higher unemployment. The Beveridge curve shifts downwards and to the right in $U/L - V/L$ space while the wage curve shifts upwards and to the right in $U/L - w/F$ space. The effect is substantial. For example, when the bargaining power $\beta$ varies between 0 and 0.6, the rate of unemployment varies from 1% to 11%. This, in effect, is a quantification of the idea – often raised in the context of the discussion of U.S.-Europe unemployment differences – that greater worker wage bargaining power is detrimental to employment.

8 Market Efficiency

Hosios (1990) has shown that under certain conditions the market is efficient if the contribution of unemployed workers to matching equals the workers’ share in the match surplus. This efficiency condition balances the negative congestion and positive trading externalities induced by search. The estimates in Tables 2 and 3 above indicate that the share of workers in the surplus is around 0.07-0.15. Yashiv (2000a) provides estimates of the matching function in the same period with the same data set. The estimates indicate that the matching function exhibits increasing returns to scale, a finding which is inconsistent with the conditions needed – constant returns to scale in matching among them – for the Hosios result. However the departure from constant returns to scale is not big. According to the matching function estimates the contribution of workers to matching is around 0.20-0.25 under one specification and 0.01-0.05 under another. Hence, comparing the two sets of estimates [Tables 2 and 3 here and Yashiv (2000a)], workers got in wages roughly what they contributed to matching, implying market efficiency, or just small departures from it.
9 Conclusions

The findings of this paper lend empirical support to the modelling of wage formation as a bargaining process against the backdrop of frictions. They serve to indicate how empirically valid is the model and to quantify the wage formation process, an investigation hitherto unexplored. The results show that the value of unemployment plays a key role. It is driven by net unemployment benefits and even more by a term capturing home production or production in the non-formal sector and any non-pecuniary value. A simulation analysis showed that well-defined Beveridge and wage curves are generated by the model’s steady state. The curves were structurally characterized and it was shown how key variables and parameters in the wage bargaining process affect them. In particular, increases in the value of unemployment were shown to lead to higher wages, lower job creation and higher unemployment. Quantifying these changes in a calibrated framework indicated that substantial increases in equilibrium unemployment may occur for reasonable variation in bargaining parameters. The extent of efficiency in this market was also empirically evaluated, revealing at most a small departure from efficiency.

The paper provides a framework that may be useful in further evaluating policy schemes. Thus the effects of UI and taxation policies on wages, job vacancy creation and unemployment may be studied. Another area for future research is the examination of cross-country differences such as U.S.-Europe differences, where unemployment benefits and labor taxation have been often cited as explanatory variables. Such a study is evidently predicated on the availability of relevant data; the type of data needed is implied by the current analysis.
References


10 Appendix A

Derivation of the Wage Equation and Match Surplus Sharing

The following derivation is based on Nash (1950) and its application to the search and matching context by Diamond (1982a).

10.1 Asset Values

In order to derive the solution the relevant asset value expressions need to be derived.

A match that is formed and is to begin production at time $t$ is worth to the firm:

$$J^F_t = \frac{\partial F_t}{\partial n_t} - w_t(1 + \tau_t^s) - \frac{\partial \Gamma_t}{\partial n_t} + E_t \frac{1}{1 + r_t} [(1 - s_t)J^F_{t+1} + s_tJ^V_{t+1}]$$  \hspace{1cm} (35)

The value of a vacancy is:

$$J^V_t = -\frac{\partial \Gamma_t}{\partial v_t} + E_t \frac{1}{1 + r_t} [q_tJ^F_{t+1} + (1 - q_t)J^V_{t+1}]$$  \hspace{1cm} (36)

Due to free entry the following obtains:

$$J^V_t = 0$$  \hspace{1cm} (37)

For the unemployed worker the present value of unemployment consists of the sum of (i) the net value of unemployment at time $t$ ($b_t$) and (ii) the expected future value which takes into account the probability of matching into employment the next period, and the continuation value of employment $J^N$:

$$J^U_t = b_t + E_t \frac{1}{1 + r_t} [p_tJ^N_{t+1} + (1 - p_t)J^U_{t+1}]$$  \hspace{1cm} (38)

Similarly the present value of employment consists of the sum of (i) the net wage at time $t$; and (ii) the expected future value which takes into account the probability of separating from em-
ployment into unemployment in the next period, \( s_{t+1} \), and the continuation value of unemployment \( J^U \):

\[
J_t^N = w_t(1 - \tau_t) + E_t \frac{1}{1 + r_t} \left[ (1 - s_t)J_{t+1}^N + s_tJ_{t+1}^U \right] \quad (39)
\]

The net value of the match for the worker is thus:

\[
J_t^N - J_t^U = w_t(1 - \tau_t) - b_t + E_t \frac{(1 - s_t - p_t)}{1 + r_t}(J_{t+1}^N - J_{t+1}^U) \quad (40)
\]

### 10.2 The Nash problem

The Nash bargaining problem is given by:

\[
w_t = \arg \max (J_t^N - J_t^U)^{\beta_t}(J_t^F - J_t^V)^{1-\beta_t} \quad (41)
\]

To derive the solution take logs of the relevant expression i.e.:

\[
\beta_t \ln(J_t^N - J_t^U) + (1 - \beta_t) \ln(J_t^F - J_t^V) \quad (42)
\]

Differentiating with respect to \( w \) and setting equal to zero:

\[
\beta_t \frac{\partial (J_t^N - J_t^U)}{\partial w_t} \bigg|_{J_t^F}^{J_t^V} + (1 - \beta_t) \frac{\partial (J_t^F - J_t^V)}{\partial w_t} = 0 \quad (43)
\]

The relevant derivatives are:

\[
\frac{\partial (J_t^F - J_t^V)}{\partial w_t} = - (1 + \tau_t^t)
\]

\[
\frac{\partial (J_t^N - J_t^U)}{\partial w_t} = (1 - \tau_t)
\]

Thus (43) becomes:
\[ \beta_t \frac{(1 - \tau_t)}{J_t^N - J_t^U} = (1 - \beta_t) \frac{(1 + \tau_t)}{J_t^F - J_t^N} \]  \hspace{1cm} (44)

10.3 The wage equation and surplus division

Inserting the asset value expressions into the Nash solution (44) one gets:

\[ \beta_t(1 - \tau_t) \left[ \frac{\partial F_t}{\partial n_t} - w_t(1 + \tau_t) - \frac{\partial \Gamma_t}{\partial n_t} + E_t \frac{1}{1 + r_t} \left[ (1 - s_t) J_{t+1}^{F} + s_t J_{t+1}^{V} \right] \right] = (1 - \beta_t)(1 + \tau_t) \left[ w_t(1 - \tau_t) - b_t + E_t \frac{(1 - s_t - p_t)}{1 + r_t} (J_t^{N} - J_t^{U}) \right] \]  \hspace{1cm} (45)

Rearranging:

\[ w_t \left[ (1 - \beta_t)(1 - \tau_t)(1 + \tau_t^S) + \beta_t(1 - \tau_t)(1 + \tau_t^S) \right] = \beta_t(1 - \tau_t) \left[ \frac{\partial F_t}{\partial n_t} - \frac{\partial \Gamma_t}{\partial n_t} \right] + (1 - \beta_t)(1 + \tau_t^S) b_t + \beta_t(1 - \tau_t) E_t \frac{1}{1 + r_t} \left[ (1 - s_t) J_{t+1}^{F} \right] - (1 - \beta_t)(1 + \tau_t^S) E_t \frac{(1 - s_t - p_t)}{1 + r_t} (J_t^{N} - J_t^{U}) \]  \hspace{1cm} (46)

Noting that (44) holds true at \( t + 1 \) i.e.:

\[ \beta_t(1 - \tau_t) J_{t+1}^{F} = (1 - \beta_t)(1 + \tau_t^S) [ J_{t+1}^{N} - J_{t+1}^{U} ] \]

We get:

\[ w_t \left[ (1 - \beta_t)(1 - \tau_t)(1 + \tau_t^S) + \beta_t(1 - \tau_t)(1 + \tau_t^S) \right] = \beta_t(1 - \tau_t) \left[ \frac{\partial F_t}{\partial n_t} - \frac{\partial \Gamma_t}{\partial n_t} \right] + (1 - \beta_t)(1 + \tau_t^S) b_t + (1 - \beta_t)(1 + \tau_t^S) E_t \frac{p_t}{1 + r_t} (J_t^{N} - J_t^{U}) \]
Hence:

\[
wt [(1 - \beta_t)(1 - \tau_t)(1 + \tau^S_t) + \beta_t(1 - \tau_t)(1 + \tau^S_t)] = \beta_t(1 - \tau_t) \left[ \frac{\partial F_t}{\partial n_t} - \frac{\partial \Gamma_t}{\partial n_t} + E_t \frac{p_t}{1 + \tau_t} J^{F+1}_t \right]
\]

\[+ (1 - \beta_t)(1 + \tau^S_t) b_t \]

Solving for \( w_t \):

\[
w_t = \frac{\beta_t}{(1 + \tau_t)} \left[ \frac{\partial F_t}{\partial n_t} - \frac{\partial \Gamma_t}{\partial n_t} + E_t \frac{p_t}{1 + \tau_t} J^{F+1}_t \right] + \frac{(1 - \beta_t)}{(1 - \tau_t)} b_t \]  \hspace{1cm} (49)

This is equation (13) in the text.

Note that the match surplus is given by:

\[
S_t = J^F_t + J^N_t - J^U_t \]  \hspace{1cm} (50)

Using (44):

\[
\beta_t J^F_t = \frac{(1 - \beta_t)(1 + \tau^S_t)}{1 - \tau_t} \left[ J^N_t - J^U_t \right]
\]

\[= \frac{(1 - \beta_t)(1 + \tau^S_t)}{1 - \tau_t} \left[ S_t - J^F_t \right] \]

Thus the surplus is given by:

\[
S_t = \frac{1 - \beta_t \tau_t + \tau^S_t (1 - \beta_t)}{(1 - \beta_t)(1 + \tau^S_t)} J^F_t \]  \hspace{1cm} (51)

Rent sharing is therefore defined as follows:

\[
\frac{J^F_t}{S_t} = \frac{(1 + \tau^S_t)}{1 - \beta_t \tau_t + \tau^S_t (1 - \beta_t)} (1 - \beta_t) \]

\[
\frac{J^N_t - J^U_t}{S_t} = \frac{(1 - \tau_t)}{1 - \beta_t \tau_t + \tau^S_t (1 - \beta_t)} \beta_t \]  \hspace{1cm} (52)

39
11 Appendix B

Data - Sources and Definitions

The data set is comprised of monthly observations. Some are available for the period 1976:01-1989:12 (n=168) and some for a longer period 1976:01-2001:12 (n=312).

The following abbreviations are used for the agencies that are the sources of the data:


1. Vacancies ($V$), unemployment ($U$) and matches ($H$):

Source: ES. Number of vacancies posted by firms, number of workseekers who registered at the ES, and number of vacancies matched respectively. The vacancies and unemployment series are the sum of end of month stocks (unfilled vacancies and unreferred workseekers) and within the month inflows (total vacancies less unfilled vacancies of the previous month and total workseekers less unreferred workseekers of the previous month).

2. Business sector employment ($N$):

Source: LFS of the CBS. Number of employess in the business sector.

3. Separation rate ($s$):

Source: computed on the basis of CBS and ES series. There is no direct gross flow measure of worker separations. We use the firms’ budget constraint (5) to solve for $s$ at each period. For $N$ we use the above measure. As ES data does not capture all hires made we also explore an alternative definition of $s$ where we double the number of ES matches. Thus the true $s$ should be between the first and the second measure.
4. Average product \((F/N)\):

Source: CBS, NIA. Net domestic product of the business sector divided by business sector employment (the above \(N\)). The net product is obtained by subtracting depreciation and net production taxes from GDP (note that \(F\) represents firms’ income in the model). As these data are not available but on annual basis, we assume that it is fixed within the year. The product and employment series are quarterly and are transformed into the monthly frequency by assuming linear geometric growth within the quarter.

5. Wages \((w)\):

Source: NIA. The average wage for employee post in the business sector.

6. Employer taxes and contributions \((\tau^*)\):

Source: NIA. Employer taxes and social security contributions levied from wages. The series is available at the annual frequency. In estimation we assume it is fixed throughout the year.

7. Worker wage taxes \((\tau)\):

Source: BOI. Taxes and net social security contributions (i.e net of benefits received) by workers levied from wages. Here to the data are annual and we assume constancy within the year.

8. Unemployment benefits \((z)\):

Source: NIA. The monthly average of nominal unemployment benefits per person. This is obtained by dividing total benefit payments by the total number of days paid for the entire relevant population (benefits are paid on a working day basis) and then multiplying by 25, which is the average number of working days a month. The series represent what a person would get on average if unemployed.

9. The real rate of interest \((r)\):

Source: BOI, CBS. \((1+ \text{the basic nominal interest rate charged by banks})/(1 + \text{the rate of business sector GDP deflator inflation})\). The numerator is the most reliable nominal interest rate series in the sample period and is the benchmark rate on bank credit to firms and households.
10. The participation rate ($\frac{L}{POP}$):
Source: LFS of the CBS. Labor force participants as a fraction of working-age population.
### Table 1

**Data Summary Statistics**

**monthly**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
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<td>$\frac{wN}{F}$</td>
<td>real unit labor costs or the labor share of income</td>
<td>0.53</td>
<td>0.06</td>
<td>0.54</td>
<td>0.05</td>
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<td>$\frac{w(1+\tau_s)N}{F}$</td>
<td>labor share of income including employer’s taxes</td>
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<td>0.05</td>
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<td>–</td>
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<td>$\frac{V}{F}$</td>
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<td>–</td>
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<td>–</td>
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<td>0.11</td>
<td>0.05</td>
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<td>$\tau$</td>
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<td>0.02</td>
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**Note:** Appendix B elaborates on data sources and definitions.
Table 2
GMM Estimation

I Firms’ Euler equation

\[ \frac{\gamma_1 (\psi \frac{V_t}{F_t} + (1 - \psi) \frac{Q_t V_t}{F_t}) \gamma_2 - 1 (\psi + (1 - \psi) Q_t) \frac{F_t}{L_t}}{Q_t} \]

\[ = \frac{1}{1 + r_t} \frac{N_{t+1}}{N_t} \left[ \alpha \left( 1 - \left[ \frac{\gamma_1 (\psi \frac{V_{t+1}}{F_t} + (1 - \psi) \frac{Q_{t+1} V_{t+1}}{F_t}) \gamma_2 - 1 (\psi + (1 - \psi) Q_{t+1}) \frac{F_{t+1}}{L_{t+1}}}{Q_{t+1}} \right. \right. \\
\left. \left. + (1 - s_{t+1}) \gamma_1 (\psi \frac{V_{t+1}}{F_{t+1}} + (1 - \psi) \frac{Q_{t+1} V_{t+1}}{F_{t+1}}) \gamma_2 - 1 (\psi + (1 - \psi) N_{t+1} + (1 - \psi)) \frac{N_{t+1}}{F_{t+1}} \right) \right] \]

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<th></th>
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<th>2</th>
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<td>(\gamma_1)</td>
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<td>281,532</td>
</tr>
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<td></td>
<td>(127,282)</td>
<td>(190,363)</td>
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<td>(\gamma_2)</td>
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<td>((8 \times 10^{-6}))</td>
<td>((2 \times 10^{-4}))</td>
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<td>(\alpha)</td>
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<td>0.62</td>
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</tr>
<tr>
<td>(a)</td>
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Notes:
2. Instruments used are a constant and 6 lags of \(\frac{w}{F/N}\) and \(\frac{QV}{L}\).
4. The parameter \(\psi\) is either constrained (denoted in bold letters) or estimated using \(\psi = \frac{e^a}{1+e^a}\).
II Wage equation

\[
\ln w_t - \ln \left( \frac{F_t}{N_t} \right) = \ln B_t + j_t
\]

\[
B_t = \frac{\beta_t}{(1 + \tau_t^2)} \left( \alpha \left( 1 - \left[ \frac{\mu_1}{\gamma_2} (\psi \frac{V_t}{L_t} + (1 - \psi) \frac{Q_t V_t}{L_t}) \gamma_1 \right] \right) + \frac{\mu_1}{\gamma_2} (\psi \frac{V_t}{L_t} + (1 - \psi) \frac{Q_t V_t}{L_t})^{\gamma_1 - 1} (\psi + (1 - \psi) Q_t) \frac{N_t}{L_t} \right)
\]

\[
+ \frac{(1 - \beta_t)}{(1 - \tau_t)} \frac{b_t}{\frac{F_t}{N_t}}
\]

a. Alternative Specifications of \( b_t \)

\[
b_t = \frac{z_t}{F_t} (1 - \tau_t) + \frac{x_t}{F_t} \frac{N_t}{N_t}
\]

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<th>( \frac{X_t}{N_t} ) specification</th>
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<th>1b</th>
<th>2a</th>
<th>2b</th>
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<td>( x( \frac{L_t}{POP_t} ) )</td>
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<tr>
<td>( \mu_1 )</td>
<td>0.11</td>
<td>0.13</td>
<td></td>
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<td></td>
<td>(0.19)</td>
<td>(0.26)</td>
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<td>( \mu_2 )</td>
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<td>(0.43)</td>
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<td>0.74</td>
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</tbody>
</table>

**Notes:**


2. The following parameter values were constrained throughout: \( \alpha = 0.62, \gamma_1 = 400,000 \) (in the columns marked a) or \( 200,000 \) (in the columns marked b), \( \gamma_2 = 4.75, \psi = 0.3 \).

3. The different columns represent variations in the specification of \( \frac{x}{N_t} \) which is the second term in \( \frac{b_t}{N_t} \) as indicated in the second row, where:

\[
x( \frac{L_t}{POP_t} )^2 = \mu_1 \left( \frac{L_t}{POP_t} \right) + \mu_2 \left( \frac{L_t}{POP_t} \right)^2
\]

\[
x( \frac{L_t}{POP_t} )^{\text{male,female}} = \mu_1 \left( \frac{L_t}{POP_t} \right)^{\text{male}} + \mu_2 \left( \frac{L_t}{POP_t} \right)^{\text{female}}
\]

4. Instruments used are a constant and 3 lags of \( \frac{wn}{\bar{F}}, \frac{QV}{L} \) and \( \ln M_t - \ln M_{t-1} \).

b. Alternative Specifications of $\beta_t$

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_t = \tilde{\beta}$</td>
<td>$\beta_t = \frac{\beta V_t}{U_t}$</td>
<td>$\beta_t = \frac{1 - \beta^2}{1 - \beta + \frac{1}{\beta}}$</td>
<td>$\beta_t = \frac{\beta + \frac{1}{\beta} \beta (1 - \beta)}{1 + \frac{1}{\beta} (1 - \beta)}$</td>
<td></td>
</tr>
<tr>
<td>implied $\frac{\beta_t - \text{mean and std.}}{\text{std.}}$</td>
<td>0.31 (0.02)</td>
<td>0.33 (0.03)</td>
<td>0.33 (0.03)</td>
<td>0.33 (0.03)</td>
</tr>
<tr>
<td>$\bar{\beta}$</td>
<td>0.09 (0.08)</td>
<td>0.09 (0.05)</td>
<td>0.28 (0.11)</td>
<td>0.06 (0.04)</td>
</tr>
<tr>
<td>implied $\beta_t - \text{mean and std.}$</td>
<td>0.09 (0.08)</td>
<td>0.07 (0.04)</td>
<td>0.10 (0.01)</td>
<td>0.09 (0.01)</td>
</tr>
<tr>
<td>J-stat</td>
<td>19.7</td>
<td>18.5</td>
<td>19.4</td>
<td>19.3</td>
</tr>
<tr>
<td>p-value</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>$\rho(\text{actual $w/n$, fitted $w/n$})$</td>
<td>0.73</td>
<td>0.74</td>
<td>0.73</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Notes:


2. The following parameter values were constrained throughout: $\alpha = 0.62, \gamma_1 = 400,000, \gamma_2 = 4.75, \psi = 0.3$.

3. The columns represent variations in the specification of $\beta_t$ as indicated in the second row; the alternatives are spelled out in section 3.2.3. The specification used for $b_t$ is the one used in column 3a of Table 211a.

4. Instruments used are a constant and 3 lags of $\frac{w}{F/N}, \frac{QV}{L}$ and $(\ln M_t - \ln M_{t-1})$.

### c. Alternative instruments sets

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>instrument set</td>
<td>3lags{\frac{QV}{L}, \frac{w}{F/N}, M\ln M}</td>
<td>3lags {\frac{QV}{L}, \frac{w}{F/N}, M_i}</td>
<td>6lags{\frac{QV}{L}, \frac{w}{F/N}, M\ln M}</td>
</tr>
<tr>
<td>$\tilde{\beta}$</td>
<td>0.09</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>0.11</td>
<td>0.12</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.18)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>0.65</td>
<td>0.62</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>(0.32)</td>
<td>(0.29)</td>
<td>(0.23)</td>
</tr>
<tr>
<td>J-stat</td>
<td>19.7</td>
<td>17.6</td>
<td>34.6</td>
</tr>
<tr>
<td>p-value</td>
<td>0.01</td>
<td>0.01</td>
<td>0.004</td>
</tr>
<tr>
<td>$\rho(\text{actual fit}, \text{fitted fit})$</td>
<td>0.73</td>
<td>0.73</td>
<td>0.72</td>
</tr>
</tbody>
</table>

#### Notes:


2. The following parameter values were constrained throughout: $\alpha = 0.62, \gamma_1 = 400,000, \gamma_2 = 4.75, \psi = 0.3$.

3. The columns represent variations in the instrument set which is a constant and lags of the variables indicated in the second row. The specifications used for $\beta_t$ and $b_t$ are the ones used in column 3a of Table 2IIa.

Table 3
I Co-Integration Wage Equation Estimates

Co-integrating relation:

\[ w_t = \beta_t \frac{F_t}{N_t} + (1 - \beta_t) b_t \]

a. Unit Root Tests

<table>
<thead>
<tr>
<th></th>
<th>ADF statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w_t )</td>
<td>-1.62</td>
</tr>
<tr>
<td>( \Delta w_t )</td>
<td>-10.7</td>
</tr>
<tr>
<td>( \frac{F_t}{N_t} )</td>
<td>-1.77</td>
</tr>
<tr>
<td>( \Delta \frac{F_t}{N_t} )</td>
<td>-10.4</td>
</tr>
<tr>
<td>( z_t )</td>
<td>-1.22</td>
</tr>
<tr>
<td>( \Delta z_t )</td>
<td>-10.3</td>
</tr>
</tbody>
</table>

Note: The 10% critical value is -2.57. The 1% critical value is -3.45.
### b. Co-Integration Estimates

<table>
<thead>
<tr>
<th>$\frac{\text{z}_t}{\text{x}_t}$ specification</th>
<th>$x \left( \frac{L_t \text{POP}_{\text{male}, \text{female}}}{N_t} \right)$</th>
<th>$\mu_1$</th>
<th>$x \left( \frac{L_t \text{POP}<em>{\text{male}, \text{female}}}{N_t}, (\frac{L_t \text{POP}</em>{\text{male}, \text{female}}}{N_t})^2 \right)$</th>
<th>$x \left( \frac{L_t \text{POP}_{\text{male}, \text{female}}}{N_t} \right)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.34</td>
<td>0.23</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>0.11</td>
<td></td>
<td>1.60</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td></td>
<td>(0.11)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>0.65</td>
<td></td>
<td>-1.98</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>(0.31)</td>
<td></td>
<td>(0.20)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>implied mean of $\frac{\text{z}_t}{\text{x}_t}$</td>
<td>0.30</td>
<td>0.30</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>implied std. of $\frac{\text{z}_t}{\text{x}_t}$</td>
<td>(0.02)</td>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.75</td>
<td>0.80</td>
<td>0.81</td>
<td>0.81</td>
</tr>
<tr>
<td>$\rho(\text{actual}, \text{fitted})$</td>
<td>0.75</td>
<td>0.67</td>
<td>0.69</td>
<td>0.68</td>
</tr>
<tr>
<td>Residual ADF statistic</td>
<td>-5.49</td>
<td>-5.36</td>
<td>-5.59</td>
<td>-5.85</td>
</tr>
</tbody>
</table>

**Notes:**


2. The different columns represent variations in the specification of $\frac{\text{z}_t}{\text{x}_t}$.

## II GMM Wage Equation Estimates (long sample)

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{x_t}{N_t} ) specification</td>
<td>( \mu_1 )</td>
<td>( \mu_1 \frac{L_t}{P_t} + \mu_2 \left( \frac{L_t}{P_t} \right)^2 )</td>
<td>( \mu_1 \frac{L_t}{P_t}^{\text{male}} + \mu_2 \left( \frac{L_t}{P_t} \right)^{\text{female}} )</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.32</td>
<td>0.25</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.10)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>( \mu_1 )</td>
<td>0.30</td>
<td>1.48</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.24)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>( \mu_2 )</td>
<td></td>
<td>-1.74</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.46)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>implied mean of ( \frac{x_t}{N_t} )</td>
<td>0.32</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>implied std. of ( \frac{x_t}{N_t} )</td>
<td>–</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>J-stat</td>
<td>13.7</td>
<td>12.8</td>
<td>13.6</td>
</tr>
<tr>
<td>p-value</td>
<td>0.19</td>
<td>0.24</td>
<td>0.19</td>
</tr>
<tr>
<td>( \rho(\text{actual } \frac{\text{wnt}}{\text{fitted } \frac{\text{wnt}}{\text{f}}}) )</td>
<td>0.66</td>
<td>0.67</td>
<td>0.67</td>
</tr>
</tbody>
</table>

**Notes:**


2. The different columns represent variations in the specification of \( \frac{x_t}{N_t} \) which is the second term in \( \frac{b_t}{N_t} \) as indicated in the second row, where:

\[
x(\frac{L_t}{POP_t}, \frac{L_t}{POP_t}) = \mu_1 \frac{L_t}{POP_t} + \mu_2 \left( \frac{L_t}{POP_t} \right)^2
\]

\[
x(\frac{L_t}{POP_t}^{\text{male,female}}) = \mu_1 \left( \frac{L_t}{POP_t} \right)^{\text{male}} + \mu_2 \left( \frac{L_t}{POP_t} \right)^{\text{female}}
\]

3. Instruments used are a constant and 6 lags of \( \frac{x_t}{N_t} \) and \( (\ln P_t - \ln P_{t-1}) \).

Table 4
Wage Decomposition and Workers Bargaining Share

a. Bargaining Power and Bargaining Share

<table>
<thead>
<tr>
<th>specification</th>
<th>$\beta$</th>
<th>$\frac{J^S - J^U}{J^U}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 2IIa Column 3a</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>Table 3Ib Column 3</td>
<td>0.19</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Notes:
Each entry in the $\frac{J^S - J^U}{J^U}$ column reports the sample mean using the point estimates of the parameters from Table 2IIa or Table 3Ib.

b. Mean Decomposition

<table>
<thead>
<tr>
<th>specification</th>
<th>fitted $\frac{\mu_i}{\mu}$</th>
<th>$\frac{\beta}{11+\gamma_1}\alpha(1 - \frac{2}{\gamma_2} \psi \frac{V_t}{L_t} + (1 - \psi) \frac{Q_t V_t}{L_t})^{\gamma_2}$</th>
<th>fitted $\frac{FV_t}{\mu}$</th>
<th>fitted $\frac{(1 - \beta) \frac{Z_t}{\mu}}{\mu}$</th>
<th>fitted $\frac{{1 - \beta} \frac{W_t}{\mu}}{\mu}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 2IIa column 3a</td>
<td>0.537</td>
<td>9%</td>
<td>1%</td>
<td>28%</td>
<td>62%</td>
</tr>
<tr>
<td>Table 3Ib Column 3</td>
<td>0.542</td>
<td>20%</td>
<td>–</td>
<td>27%</td>
<td>54%</td>
</tr>
</tbody>
</table>

Notes:
1. The first column gives the fitted mean of $\frac{\mu_i}{\mu}$. The other columns give the fraction of the mean accounted for by the relevant component.
2. Actual $\frac{\mu_i}{\mu}$ has a mean of 0.544.
3. The term $FV_t$ is given by:

$$FV_t = \frac{V_t}{U_t} \gamma_1 (\psi \frac{V_t}{L_t} + (1 - \psi) \frac{Q_t V_t}{L_t})^{\gamma_2 - 1} (\psi + (1 - \psi) Q_t) \frac{N_t}{L_t}$$
c. Variance Decomposition

1. GMM estimates (Table 2IIa Column 3a)

<table>
<thead>
<tr>
<th>$\frac{w_t}{n_t}$, fitted &amp; actual</th>
<th>41%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{\beta}{(1+\tau_t)^2} \alpha A$</td>
<td>0.04%</td>
</tr>
<tr>
<td>$\frac{\beta}{(1+\tau_t)^2} FV_t$</td>
<td>-0.2%</td>
</tr>
<tr>
<td>$(1-\beta) \frac{z_t}{n_t}$</td>
<td>2%</td>
</tr>
<tr>
<td>$(1-\beta) \frac{x_t}{n_t}$</td>
<td>0.1%</td>
</tr>
</tbody>
</table>

$A \equiv \left ( 1 - \left [ \frac{\gamma_1}{\gamma_2} \psi \frac{v_t}{L_t} + (1 - \psi) \frac{w_t v_t}{L_t} \right ] \right )$

2. Co-Integration estimates (Table 3Ib Column 3)

<table>
<thead>
<tr>
<th>$\frac{w_t}{n_t}$, actual</th>
<th>66%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\frac{\beta}{(1+\tau_t)^2} \alpha A$</td>
<td>2%</td>
</tr>
<tr>
<td>$(1-\beta) \frac{z_t}{n_t}$</td>
<td>10%</td>
</tr>
<tr>
<td>$(1-\beta) \frac{x_t}{n_t}$</td>
<td>-2%</td>
</tr>
</tbody>
</table>

Note: The variance-co-variance matrices are given in terms of rates out of $\frac{w_t}{n_t}$. 53
### Table 5
Business Cycle Properties

#### a. Indicators

<table>
<thead>
<tr>
<th></th>
<th>$F^{HP}$</th>
<th>$F^{LOG}$</th>
<th>$N^{HP}$</th>
<th>$N^{LOG}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F^{HP}$</td>
<td>1</td>
<td>0.58</td>
<td>0.32</td>
<td>0.10</td>
</tr>
<tr>
<td>$F^{LOG}$</td>
<td>0.58</td>
<td>1</td>
<td>0.18</td>
<td>0.54</td>
</tr>
<tr>
<td>$N^{HP}$</td>
<td>0.32</td>
<td>0.18</td>
<td>1</td>
<td><strong>0.33</strong></td>
</tr>
<tr>
<td>$N^{LOG}$</td>
<td>0.10</td>
<td>0.54</td>
<td>0.33</td>
<td>1</td>
</tr>
</tbody>
</table>

#### b. Co-Movement (correlations)

<table>
<thead>
<tr>
<th></th>
<th>$F^{HP}$</th>
<th>$F^{LOG}$</th>
<th>$N^{HP}$</th>
<th>$N^{LOG}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w^{HP}$</td>
<td>-0.08</td>
<td>-0.05</td>
<td>0.18</td>
<td>0.04</td>
</tr>
<tr>
<td>$w^{LOG}$</td>
<td>-0.04</td>
<td>-0.47</td>
<td>0.12</td>
<td>-0.45</td>
</tr>
<tr>
<td>$w_{F/N}$</td>
<td>-0.31</td>
<td>-0.48</td>
<td>0.03</td>
<td>-0.27</td>
</tr>
<tr>
<td>$(1+\gamma)\frac{\alpha}{\beta}$</td>
<td>0.04</td>
<td>0.30</td>
<td>0.05</td>
<td>0.40</td>
</tr>
<tr>
<td>$(1-\beta)\frac{z_t}{\tau_t}$</td>
<td>-0.11</td>
<td>-0.14</td>
<td>-0.08</td>
<td>-0.10</td>
</tr>
<tr>
<td>$(1-\gamma)\frac{z_t}{\tau_t}$</td>
<td>-0.01</td>
<td>-0.28</td>
<td>0.07</td>
<td>-0.06</td>
</tr>
<tr>
<td>$z_{F/N}$</td>
<td>-0.12</td>
<td>-0.21</td>
<td>-0.09</td>
<td>-0.13</td>
</tr>
<tr>
<td>$z_{F/N}$</td>
<td>-0.01</td>
<td>-0.10</td>
<td>0.07</td>
<td>-0.28</td>
</tr>
</tbody>
</table>

**Notes:**

1. $HP$ denotes an HP-filtered variable in logs. $LOG$ denotes a log-linearly detrended variable.
Figure 1a: Unit labor costs (inclusive of employer taxes) \( \frac{w(1+\tau_s)}{F/N} \)

Figure 1b: Replacement ratio \( \frac{z}{w} \)
Figure 2a,b
Wage Curve and Beveridge Curve – variations in $r \in [0.001, 0.015]$
Figure 2c,d
Wage Curve and Beveridge Curve – variations in $g^f \in [0, 0.005]$
Figure 3a,b
Wage Curve and Beveridge Curve – variations in $\beta \in [0, 0.6]$
Figure 3c,d

Wage Curve and Beveridge Curve – variations in $b \in [0.44, 0.48]$