

Aggregate Hiring and the Value of Jobs Along the Business Cycle

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Abstract

U.S. CPS data indicate that in recessions firms actually *increase* their hiring rates from the pools of the unemployed and out of the labor force. Why so? The paper provides an explanation by studying the optimal recruiting behavior of the representative firm. The model combines labor frictions, of the search and matching type, with capital frictions, of the q-model type.

Optimal firm behavior is a function of the value of jobs, i.e., the expected present value of the marginal worker to the firm. These are estimated to be counter-cyclical, the underlying reason being the dynamic behavior of the labor share of GDP. The counter-cyclicity of hiring rates and job values, which may appear counter-intuitive, is shown to be consistent with well-known business cycle facts. The analysis emphasizes the difference between current labor productivity and the wider, forward-looking concept of job values.

The paper explains the high volatility of firm recruiting behavior, as well as the reduction over time in labor market fluidity in the U.S., using the same estimated model. Part of the explanation has to do with job values and another part with the interaction of hiring and investment costs, both determinants having been typically overlooked.

Key words: counter-cyclical job values, business cycles, aggregate hiring, , vacancies, labor market frictions, capital market frictions, volatility, labor market fluidity.

JEL codes: E24, E32

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1 Introduction

The paper asks what governs the representative firm hiring behavior along the business cycle. This behavior is important for our understanding of business cycles and employment dynamics. The literature on this topic has devoted an enormous amount of attention, for over a decade, to the ability of models to account for the high volatility of job vacancies and unemployment, and has paid much less attention to the counter-cyclical of the hiring rate from non-employment observed in U.S. data. This paper shows that a model combining labor frictions, of the search and matching type, with capital frictions, of the q-model type, can account for both the high volatility of job vacancy rates and the counter-cyclical of hiring rates from non-employment. The results of estimation are shown to be consistent with well-known business cycle facts, such as pro-cyclical employment and pro-cyclical vacancy and job-finding rates, as well as job to job flows. The analysis emphasizes the difference between the behavior of current labor productivity and the wider, forward-looking concept of job value.

I look at the optimality equation of the firm, which equates the marginal cost of worker recruitment and the expected present value of the worker for the firm, i.e., the job value. I estimate alternative specifications of the equation. Estimation rests on key formulations in the literature, particularly the ones related to search and matching and investment q models. Following estimation, I analyze the cyclical behavior and volatility of job values and of the recruiting variables.

The main findings are as follows:

(i) Job values are counter-cyclical in U.S. data. This key finding means that in recessions the value of jobs for firms goes *up*. Note that this value is a forward-looking expected present value of future labor profitability.

(ii) Correspondingly, hiring rates from non-employment (unemployment + out of the labor force) are counter-cyclical: it is worthwhile for firms to increase hiring rates as job values rise in recessions.

(iii) While the afore-mentioned hiring rates are counter-cyclical, vacancy rates and hiring rates from employment (i.e., job to job flows) are pro-cyclical. The differences

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between points (ii) and (iii) are explained.

(iv) While point (i), the counter-cyclicity of job values, may appear counter-intuitive, it is consistent with the findings of recent studies looking at the cyclical behavior of the labor share in GDP. It is the dynamic behavior of the labor share that engenders the counter-cyclicity of the forward-looking job values.

(v) Points (i) and (ii) do not contradict what we already know about the cyclical features of the labor market, including pro-cyclical employment job finding rates, and wages.

(vi) Moving from cyclicity to volatility, the high volatility of vacancy and hiring rates is explained within the same framework. Part of the explanation has to do with job values and another part with the interaction of recruitment behavior with capital investment behavior. Both determinants have been typically overlooked.

(vii) The secular phenomenon of a reduction in labor market fluidity in the U.S. over time, noted by Davis and Haltiwanger (2014), is also accounted for, using the same framework.

The paper proceeds as follows: Section 2 presents the context of the paper in the literature. Section 3 presents the model and the key relations to be examined empirically. Section 4 studies the cyclical behavior of the key data series. The data and methodology are elaborated in Section 5, followed by the results of estimation in Section 6. The cyclical implications of the results are elaborated in Section 7. Section 8 elaborates on the connections of the results to the cyclicity of the labor share in GDP, recently discussed in other Macro contexts. Section 9 studies the volatility of the recruitment series (vacancy and hiring rates) and relates them to the estimated job values. In Section 10 I use this framework to explain the decline in U.S. labor market fluidity. Section 11 concludes. Derivations and other technical matters are relegated to appendices.

2 The Paper in the Context of the Literature

This paper focuses on the firms' optimal recruiting behavior in the presence of frictions in an aggregate context along the business cycle. To see how recent literature has approached this topic, it may be useful to discuss this behavior using the following simple equation:

$$MC_t(\cdot) = E_t PV_t(\cdot) \tag{1}$$

The equation relates the marginal costs of vacancies or of hiring which the firm faces

with the marginal benefit, which is the expected present value of what the firm will get from the employment relationship. In search and matching models this is usually the free entry condition. Table 1 lists 13 key studies and reports what these studies have posited with respect to the LHS and the RHS of equation (1). Appendix A presents the full equation as formulated by each study. The studies are divided into two groups – those positing linear costs and those positing convex costs.

Table 1

Beyond the differences between linear and convex costs, the table shows that the different permutations of formulating the equation include:

- (i) Single job vs large firms.
- (ii) Using vacancies or actual hires as arguments of the cost function.
- (iii) Formulating labor only or capital and labor as determining productivity.
- (iv) Wages (appearing on the RHS) being determined by the Nash solution, intrafirm bargaining, credible bargaining or sticky wage mechanisms.
- (v) Worker separations modeled as exogenous or endogenous, constant or stochastic.
- (vi) Discounting the future with a constant or time-varying rate; for the latter, there are different formulations (IMRS, WACC or derived from the stock market).

The current paper looks at a number of alternative specifications. The key one has large firms and convex costs; takes into account both vacancies and actual hires as arguments of the cost function; includes capital as well as labor; models capital adjustment frictions as well as labor frictions; uses actual wages and separation rates, without explicitly modelling how they are determined; and uses a time-varying IMRS-type discount rate. The idea is to structurally estimate this equation (and any accompanying one) in order to explore the cyclicity and volatility of aggregate recruitment behavior.

In previous work – Merz and Yashiv (2007) and Yashiv (2016) – I have also used this formulation, or special cases of it.

The former paper did so in the context of studying the determinants of the market value of U.S. firms. The idea there is that the value of investment and the value of hiring make up the value of the firm. That paper thus focuses on matching stock market values and uses relevant financial data in estimation. The current paper does not deal at all with stock market issues and does not use financial data.

The latter paper uses the formulation above to analyze the joint, forward-looking behavior of hiring and investment. It looks at their inter-relationships and the determinants of their inter-connected present values. It takes a Finance-like approach in

treating job values and capital values akin to stock prices. The empirical work is a VAR forecast analysis which allows for the determination of the relative importance of various variables in accounting for these “stock prices.” Hence it decomposes job and capital values into “dividend” and “discounting” components, as the Finance literature does.

The current paper focuses on job values only and the key issue is firm recruiting behavior over the business cycle. In particular, the current paper (i) explores the cyclical behavior of the key series related to recruiting; (ii) relates job value behavior to the labor share over the cycle; (iii) explores the relationship between the different recruiting series – vacancy rates and two hiring rate series – and job values along the cycle; (iv) shows that the standard search and matching model is not able to account for the cyclical patterns; (v) shows how the current model explains the high volatility of the recruitment rates; (vi) studies the secular decline in labor market fluidity, including recruiting.

Thus, the reader learns different lessons: Merz and Yashiv (2007) show that stock prices/values of firms depend on capital and job values and quantify these relations. Yashiv (2016) shows the complementarity between the hiring and investment processes; the important cross effects of the value of capital on the mean and the volatility of the hiring rate, and vice versa; and that future returns play a dominant role in determining capital and job values. The current paper shows that hiring rates from non-employment are counter-cyclical, following the counter-cyclicity of job values; it shows that the underlying reason is the dynamic behavior of the labor share of GDP; and that while this counter-cyclicity may appear counter-intuitive, it is consistent with well-known business cycle facts; and it shows that the same model can account for high volatility and the secular decline of the recruiting variables.

3 The Model

I present a model of firm optimization, which includes capital as well as labor, and formulate the costs function underlying the problem in such a way that the cases shown in Table 1 above will mostly be special cases.

3.1 The General Model

Set-Up. There are identical workers and identical firms, who live forever and have rational expectations.

Worker Flows. Consider worker flows. The flow from non-employment – unemployment (U) and out of the labor force (O) – to employment, E , is to be denoted $OE + UE$ and the separation flow in the opposite direction, $EU + EO$. Worker flows within employment – i.e., job to job flows – are to be denoted EE .

I shall denote:

$$\begin{aligned} \frac{h}{n} &= \left(\frac{h^1}{n}\right) + \left(\frac{h^2}{n}\right) \\ \frac{h^1}{n} &= \frac{OE + UE}{E}; \quad \frac{h^2}{n} = \frac{EE}{E} \end{aligned} \quad (2)$$

Hence h^1 and h^2 denote flows from non-employment and from other employment, respectively, and n is employment.

Separation rates are given in an analogous way by:

$$\begin{aligned} \psi &= \psi^1 + \psi^2 \\ \psi^1 &= \frac{EO + EU}{E}; \quad \psi^2 = \frac{EE}{E} = \frac{h^2}{n} \end{aligned} \quad (3)$$

Employment dynamics are thus given by:

$$\begin{aligned} n_{t+1} &= (1 - \psi_t^1 - \psi_t^2)n_t + h_t^1 + h_t^2 \\ &= (1 - \psi_t)n_t + h_t, \quad 0 \leq \psi_t \leq 1 \\ h_t^2 &= \psi_t^2 n_t \end{aligned} \quad (4)$$

*Matching and Separations.*² Firms hire from non-employment (h_t^1) and from other firms (h_t^2). Each period, the worker's effective units of labor (normally 1 per person) depreciate to 0, in the current firm, with some exogenous probability ψ_t . Thus, the match suffers an irreversible idiosyncratic shock that makes it no longer viable. The worker may be reallocated to a new firm where his/her productivity is (temporarily) restored to 1. This happens with a probability of ψ_t^2 . Those who are not reallocated join unemployment, with probability $\psi_t^1 = \psi_t - \psi_t^2$. So the fraction ψ_t^2 that enters job to job flows depends on the endogenous hiring flow h_t^2 . The firm decides how many vacancies v_t to open and, given job filling rates (q_t^1, q_t^2), will get to hire from the pre-

²I am indebted to Giuseppe Moscarini for very useful suggestions to this sub-section.

existing non-employed and from the pool of matches just gone sour. The job-filling or matching rates satisfy:

$$q_t^1 = \frac{h_t^1}{v_t}; \quad q_t^2 = \frac{h_t^2}{v_t}; \quad q_t = q_t^1 + q_t^2$$

Firms Optimization. Firms make gross investment (i_t) and vacancy (v_t) decisions. Once a new worker is hired, the firm pays him or her a per-period wage w_t . Firms use physical capital (k_t) and labor (n_t) as inputs in order to produce output goods y_t according to a constant-returns-to-scale production function f with productivity shock z_t :

$$y_t = f(z_t, n_t, k_t), \quad (5)$$

Gross hiring and gross investment are subject to frictions, spelled out below, and hence are costly activities. I represent these costs by a function $g[i_t, k_t, v_t, h_t, n_t]$ which is convex in the firm's decision variables (i_t, v_t) and exhibits constant returns-to-scale, allowing hiring costs and investment costs to interact.

In every period t , the capital stock depreciates at the rate δ_t and is augmented by new investment i_t . Similarly, workers separate at the rate ψ_t and the employment stock is augmented by new hires $q_t v_t = h_t$. The laws of motion are:

$$k_{t+1} = (1 - \delta_t)k_t + i_t, \quad 0 \leq \delta_t \leq 1. \quad (6)$$

$$n_{t+1} = (1 - \psi_t)n_t + q_t v_t, \quad 0 \leq \psi_t \leq 1 \quad (7)$$

The representative firm chooses sequences of i_t and v_t in order to maximize its profits as follows:

$$\max_{\{i_{t+j}, v_{t+j}\}} E_t \sum_{j=0}^{\infty} \left(\prod_{i=0}^j \rho_{t+i} \right) (1 - \tau_{t+j}) \left(\begin{array}{l} f(z_{t+j}, n_{t+j}, k_{t+j}) - g(i_{t+j}, k_{t+j}, v_{t+j}, h_{t+j}, n_{t+j}) \\ -w_{t+j}n_{t+j} - \left(1 - \chi_{t+j} - \tau_{t+j}D_{t+j}\right) \tilde{p}_{t+j}^I i_{t+j} \end{array} \right) \quad (8)$$

subject to the constraints (6) and (7), where τ_t is the corporate income tax rate, w_t is the wage, χ_t the investment tax credit, D_t the present discounted value of capital depreciation allowances, \tilde{p}_t^I the real pre-tax price of investment goods, and ρ_{t+j} is a time-varying discount factor. The firm takes the paths of the variables $q_t, w_t, \psi_t, \tilde{p}_t^I, \delta_t, \tau_t$ and ρ_t as given. This is consistent with the standard models in the search and matching and Tobin's q literatures. The Lagrange multipliers associated with these two constraints are denoted Q_{t+j}^K and Q_{t+j}^N , respectively. These Lagrange multipliers can be interpreted

as marginal Q for physical capital, and marginal Q for employment, respectively. I shall use the term capital value or present value of investment for the former and job value or present value of hiring for the latter.

The first-order conditions for dynamic optimality are:³

$$Q_t^K = E_t \left[\rho_{t+1} \left[(1 - \tau_{t+1}) (f_{k_{t+1}} - g_{k_{t+1}}) + (1 - \delta_{t+1}) Q_{t+1}^K \right] \right] \quad (9)$$

$$Q_t^K = (1 - \tau_t) (g_{i_t} + p_t^I) \quad (10)$$

$$Q_t^N = E_t \left[\rho_{t+1} \left[(1 - \tau_{t+1}) (f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1}) + (1 - \psi_{t+1}) Q_{t+1}^N \right] \right] \quad (11)$$

$$Q_t^N = (1 - \tau_t) \frac{g_{v_t}}{q_t} \quad (12)$$

Using these equations, the following expression captures the RHS of equation (1), the present value of the job to the firm:

$$PV_t = \rho_{t+1} (1 - \tau_{t+1}) \left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ + (1 - \psi_{t+1}) \frac{g_{v_{t+1}}}{q_{t+1}} \end{array} \right] \quad (13)$$

Basically PV_t is the present value of the profit flows from the marginal worker $f_{n_{t+j}} - g_{n_{t+j}} - w_{t+j}$ for $j = 1 \dots \infty$ adjusted for taxes (τ_{t+j}) and separation rates (ψ_{t+j}).

I can summarize the firm's first-order necessary conditions from equations (9)-(12) by the following two expressions:

$$(1 - \tau_t) (g_{i_t} + p_t^I) = E_t \left[\rho_{t,t+1} (1 - \tau_{t+1}) \left[\begin{array}{c} f_{k_{t+1}} - g_{k_{t+1}} \\ + (1 - \delta_{t+1}) (g_{i_{t+1}} + p_{t+1}^I) \end{array} \right] \right] \quad (14)$$

$$(1 - \tau_t) \frac{g_{v_t}}{q_t} = E_t \left[\rho_{t,t+1} (1 - \tau_{t+1}) \left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ + (1 - \psi_{t+1}) \frac{g_{v_{t+1}}}{q_{t+1}} \end{array} \right] \right] \quad (15)$$

Equation (15) is at the focal point of the analysis and gives structure to equation (1) above. Following the explicit formulation of the costs function g I shall consider alternative, specific cases. Equation (14) is estimated jointly with equation (15). The estimating equations are spelled out in Appendix B.

The costs function g , capturing the different frictions in the hiring and investment

³where I use the real after-tax price of investment goods, given by:

$$p_{t+j}^I = \frac{1 - \chi_{t+j} - \tau_{t+j} D_{t+j}}{1 - \tau_{t+j}} \bar{p}_{t+j}^I.$$

processes, is at the focus of the estimation work. Specifically, hiring costs include costs of advertising, screening and testing, matching frictions, training costs and more. Investment involves implementation costs, financial premia on certain projects, capital installation costs, learning the use of new equipment, etc. Both activities may involve, in addition to production disruption, the implementation of new organizational structures within the firm and new production techniques.⁴ In sum g is meant to capture all the frictions involved in getting workers to work and capital to operate in production, and not, say, just capital adjustment costs or vacancy costs. One should keep in mind that this is formulated as the costs function of the representative firm within a macroeconomic model, and not one of a single firm in a heterogenous firms micro set-up.

Functional Form. The parametric form I use is the following, generalized convex function.

$$g(\cdot) = \left[\begin{array}{l} \frac{e_1}{\eta_1} \left(\frac{i_t}{k_t} \right) \eta_1 \\ + \frac{e_2}{\eta_2} \left[\frac{(1-\lambda_1-\lambda_2)v_t + \lambda_1 q_t^1 v_t + \lambda_2 q_t^2 v_t}{n_t} \right] \eta_2 \\ + \frac{e_{31}}{\eta_{31}} \left(\frac{i_t}{k_t} \frac{q_t^1 v_t}{n_t} \right) \eta_{31} + \frac{e_{32}}{\eta_{32}} \left(\frac{i_t}{k_t} \frac{q_t^2 v_t}{n_t} \right) \eta_{32} \end{array} \right] f(z_t, n_t, k_t). \quad (16)$$

The basic idea is of a convex function of the rates of activity – investment $\left(\frac{i_t}{k_t}\right)$ and recruiting $\left(\frac{(1-\lambda_1-\lambda_2)v_t + \lambda_1 h_t^1 + \lambda_2 h_t^2}{n_t}\right)$. This function is linearly homogenous in its arguments i, k, v, h, n . The parameters $e_l, l = 1, 2, 31, 32$ express scale, and the parameters $\eta_1, \eta_2, \eta_{31}, \eta_{32}$ express the convexity of the costs function with respect to its different arguments. λ_1 is the weight in the cost function assigned to hiring from non-employment $\left(\frac{h_t^1}{n_t}\right)$, λ_2 is the weight assigned to hiring from other firms $\left(\frac{h_t^2}{n_t}\right)$, and $(1 - \lambda_1 - \lambda_2)$ is the weight assigned to vacancy $\left(\frac{v_t}{n_t}\right)$ costs. The weights λ_1 and λ_2 are thus related to the training and production disruption aspects, while the complementary weight is related to the vacancy creation aspect. The last two terms in square brackets capture interactions between investment and hiring. For these it differentiates between interaction of hiring from employment and those of hiring from non-employment. When a parameter is estimated, there is no constraint placed on its sign or magnitude.

I rationalize the use of this form in what follows.

Background Literature. The adjustment costs function considered here is an outgrowth of a long series of papers. In the early literature, Nadiri and Rosen (1969) considered interrelated factor demand functions for labor and capital with adjustment costs. Lucas (1967) and Mortensen (1973) derived firm optimal behavior with convex adjustment costs for n factors of production. It is of interest to note Mortensen's sum-

⁴See Alexopoulos (2011) and Alexopoulos and Tombe (2012).

mary of Lucas in his footnote 4 (p. 659), stating that “Adjustment costs arise in the view of Lucas either because installation and planning involves the use of internal resources or because the firm is a monopsonist in its factor markets. Since Lucas rules out the possibility of interaction with the production process, the costs are either the value of certain perfectly variable resources used exclusively in the planning and installation processes or the premium which the firm must pay in order to obtain the factors at more rapid rates.” Lucas and Prescott (1971) embedded these convex adjustment costs in a stochastic industry equilibrium.

A recent theoretical and empirical literature has given more foundations to the investment-hiring interaction terms and the different hiring terms used here. This new literature looks at the connections between investment in capital, the hiring of workers, and organizational and management changes. A general discussion and overview of this line of research is offered by Ichniowsky and Shaw (2013) and by Lazear and Oyer (2013). One specific example is provided by Bartel, Ichniowski and Shaw (2007), who study the effects of new information technologies (IT) on productivity. They use data on plants in one narrowly defined industry, valve manufacturing. Their empirical analysis reveals, inter alia, that adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of machine operators, notably technical and problem-solving skills, and with the adoption of new human resource practices to support these skills. They show how investment in capital equipment has a variety of effects on hiring and on training, some of them contradictory. Hence, in the current context, investment and hiring interactions are relevant and could have positive or negative signs. Another example is provided by a study of a large hospital system by Bartel, Beaulieu, Phibbs, and Stone (2014). They find that the arrival of a new nurse is associated with lowered productivity. This effect is significant only if the nurse is hired externally; hence there is reason to make a distinction between job to job movements and hiring from non-employment.

Arguments of the function. This specification captures the idea that frictions or costs increase with the extent of the activity in question – vacancy creation, hiring and investment. This needs to be modelled relative to the size of the firm. The intuition is that hiring 10 workers, for example, means different levels of hiring activity for firms with 100 workers or for firms with 10,000 workers. Hence firm size, as measured by its physical capital stock or its level of employment, is taken into account and the costs function is increasing in the vacancy, hiring and investment rates, $\frac{v}{n}$, $\frac{h}{n}$ and $\frac{i}{k}$. The function used postulates that costs are proportional to output, i.e., the results can be stated in terms of lost output.

More specifically, the terms in the function presented above may be justified as follows (drawing on Garibaldi and Moen (2009)): suppose each worker i makes a recruiting and training effort h_i ; as this is to be modelled as a convex function, it is optimal to spread out the efforts equally across workers so $h_i = \frac{h}{n}$; formulating the costs as a function of these efforts and putting them in terms of output per worker one gets $c\left(\frac{h}{n}\right)\frac{f}{n}$; as n workers do it then the aggregate cost function is given by $c\left(\frac{h}{n}\right)f$.

Convexity. I use a convex function. While non-convexities were found to be significant at the micro level (plant, establishment, or firm), a number of recent papers have given empirical support for the use of a convex function in the aggregate, showing that such a formulation is appropriate at the macroeconomic level.⁵

Interaction. The terms $\frac{e_{31}}{\eta_{31}}\left(\frac{i_t q_t^1 v_t}{k_t n_t}\right)^{\eta_{31}}$ and $\frac{e_{32}}{\eta_{32}}\left(\frac{i_t q_t^2 v_t}{k_t n_t}\right)^{\eta_{32}}$ express the interaction of investment and hiring costs. They allow for a different interaction for hires from non-employment (h_t^1) and from other firms (h_t^2). These terms, absent in many studies, have important implications for the complementarity of investment and hiring.

3.2 Alternative Specifications

Beyond the general model spelled out above, which nests most of the specifications of Table 1, I specifically examine two special cases.

3.2.1 Tobin's q Approach

As shown in the second group of studies in Table 1 above, there is a formulation of optimal hiring with convex costs following the logic of the literature on investment models, mostly the seminal contributions of Lucas and Prescott (1971) and of Tobin (1969) and Hayashi (1982). This approach ignores the other factor of production (i.e., assumes no adjustment costs for it). In the current case, investment in capital is assumed to have no adjustment costs. Typically quadratic costs are posited (for vacancies and hiring). Hence in this case $e_1 = e_{31} = e_{32} = 0$ and $\eta_2 = 2$. The optimality equation becomes:

⁵Thus, Thomas (2002) and Kahn and Thomas (2008, see in particular their discussion on pages 417-421) study a dynamic, stochastic, general equilibrium model with nonconvex capital adjustment costs. One key idea which emerges from their analysis is that there are smoothing effects that result from equilibrium price changes. House (2014) shows that even though neoclassical investment models are inconsistent with micro data, they capture the relevant aggregate investment dynamics embodied in models with fixed investment adjustment costs. On page 99 he states that "This finding is highly robust and explains why researchers working in the DSGE tradition have found little role for fixed costs in numerical trials." This is due to the "The near-infinite elasticity of intertemporal substitution (which) eliminates virtually any role for microeconomic heterogeneity in governing investment demand."

$$(1 - \tau_t) \frac{e_2}{q_t} \left[\frac{(1 - \lambda_1 - \lambda_2)}{+\lambda_1 q_t^1 + \lambda_2 q_t^2} \right]^2 \frac{v_t}{n_t} = E_t \frac{1}{\frac{f_t}{n_t}} \left[\rho_{t,t+1} (1 - \tau_{t+1}) \left[\frac{f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1}}{+(1 - \psi_{t+1}) \frac{g_{v_{t+1}}}{q_{t+1}}} \right] \right] \quad (17)$$

3.2.2 The Standard Search and Matching Model

The standard search and matching model does not consider investment when formulating costs and refers to linear vacancy costs. It refers to vacancies only (not to hiring). In terms of the model above it has $e_1 = e_{31} = e_{32} = 0, \lambda_1 = \lambda_2 = 0$ and $\eta_2 = 1$. It thus formulates the optimality equation for vacancy creation (v_t) as follows, i.e., this is equation (15) for this particular model.

$$(1 - \tau_t) \frac{e_2 f_t}{q_t n_t} = E_t \left[\rho_{t+1} (1 - \tau_{t+1}) \left[f_{n_{t+1}} - w_{t+1} + (1 - \psi_{t+1}) \frac{e_2 f_{t+1}}{q_{t+1} n_{t+1}} \right] \right] \quad (18)$$

As shown in the first group of studies in Table 1 above, and further discussed in Appendix A, this is a prevalent formulation, that has total costs be a linear function of vacancies, i.e., $\frac{e_2 f_t}{q_t n_t} v_t$ whereby the cost is proportional to labor productivity $\frac{f_t}{n_t}$ and depends on the average duration of the vacancy $\frac{1}{q_t}$ (q_t is the job filling rate, $q_t = \frac{h_t}{v_t}$).

4 The Cyclical Behavior of Vacancy and Hiring Rates

Before turning to estimation, it is worthwhile to briefly examine the cyclical behavior of each of the data series themselves: hiring rates ($\frac{h_t^1}{n_t}$) from non-employment (unemployment + OLF); hiring rates ($\frac{h_t^2}{n_t}$) from employment (i.e., job to job flows); and vacancy rates ($\frac{v_t}{n_t}$). I consider each in turn.

4.1 Hiring from Non-Employment

I compute $\rho(\frac{h_t^1}{n_t}, f_{t+i})$ where h_t^1 is the CPS gross hiring flow from the pool of unemployment plus out of the labor force and f_{t+i} is Non Financial Corporate Business Sector (NFCB) GDP, in logged, HP filtered terms (see Appendix C for data definitions and sources).

Table 2 and Figure 1

Hiring rates from non-employment are *counter-cyclical*. This fact has been noted by Blanchard and Diamond (1990), Elsby, Michaels, and Solon (2009), and Shimer (2012).

4.2 Job to Job Flows

I repeat the same computation for job to job flows i.e., $\rho(\frac{h_t^2}{n_t}, f_{t+i})$ where h_t^2 is the CPS gross job to job flows, based on the work of Fallick and Fleischmann (2004), which was updated till 2013 (see Appendix C). The sample here starts in 1994.

Table 3 and Figure 2

Job to job flows, i.e., hiring rates from employment, are pro-cyclical. This is well-known; see, for example, the discussion in Fallick and Fleischmann (2004).

4.3 Vacancy Rates

I repeat the same computation for vacancy rates i.e., $\rho(\frac{v_t}{n_t}, f_{t+i})$ where v_t is the adjusted HWI rate, as delineated in the Appendix C.

Table 4 and Figure 3

Vacancy rates are pro-cyclical, as is well-known too (see Barnichon (2012)).

4.4 CPS vs JOLTS Hires Data

When using these worker flows, a natural question that arises concerns the possible use of JOLTS data. These data are not used here, as they do not allow for the breakdown of hiring into h_t^1 and h_t^2 and are available only from December 2000. Moreover, there are big differences between CPS and JOLTS data as shown in the following table that pertains to total hires $h_t = h_t^1 + h_t^2$ in the overlapping sample period.

Table 5

The following conclusions emerge from the table: the CPS mean is 1.83 times higher than the JOLTS mean, the CPS median is 1.81 times higher; the c.o.v of CPS is 0.0587, about half of c.o.v for JOLTS at 0.10; the third moment is very different; only the fourth moment is close across the data samples.

Hence one should note that these two data sets yield very different worker flow series and any comparisons need to be done with care. I do not use JOLTS data here for the reasons elaborated above.

4.5 Consistency with Well-Known Facts

The emerging picture from Figures 1-3 and Tables 2-4 is consistent with some well-known facts. Note that the hiring rate is the product of the job finding rate, the non-employment rate and the inverse of the employment rate:

$$\underbrace{\frac{h_t^1}{n_t}}_{\text{hiring rate}} = \underbrace{\frac{h_t^1}{u_t + o_t}}_{\text{job finding}} \times \underbrace{\frac{u_t + o_t}{pop_t}}_{\text{non-emp}} \times \underbrace{\frac{1}{\frac{n_t}{pop_t}}}_{\text{inv emp ratio}} \quad (19)$$

where u is unemployment, o is the out of the labor force pool and pop is the working age population.

The following table shows the co-movement statistics for these variables.

Table 6

The job finding rate $\frac{h_t^1}{u_t + o_t}$ is pro-cyclical, as is well known. The latter feature has been emphasized by Shimer (2012). The non-employment rate $\frac{u_t + o_t}{pop_t}$ and the inverse of the employment ratio $\frac{1}{\frac{n_t}{pop_t}}$ are counter-cyclical, as widely known too. At the same time the gross hiring rate $\frac{h_t^1}{n_t}$ is counter-cyclical, as shown above. The hiring rate is counter-cyclical as the counter-cyclicity of the last two variables dominates the pro-cyclicity of the job-finding rate.⁶

Also note the following. Employment dynamics are given by:

$$\frac{n_{t+1} - n_t}{n_t} = \frac{h_t^1}{n_t} - \psi_t^1 \quad (20)$$

Along the cycle the variables in (20) can be shown as follows:

Figure 4

Evidently, in the shaded NBER-dated recession periods, net employment growth is negative with separations being higher than hires. At the same time, in cyclical terms, Figure 5 shows that both rates increase – relative to the HP trend – during recessions, i.e., both are counter-cyclical.

Figure 5

⁶In this context the following quote from Shimer (2012, page 145) is pertinent: “Still, it is most important point to recognize the differential behavior of the job finding probability and the number of workers finding jobs;...”

5 Methodology and Data

In order to be empirically evaluated, the afore-going optimality equations of the firm will be estimated. I discuss the data, the estimation methodology and a post-estimation approximation and variance decomposition.

5.1 Data

The data are quarterly and pertain to the private sector of the U.S. economy. For a large part of the empirical work reported below the sample period is 1994-2013. The start date of 1994 is due to the lack of availability of job to job worker flows (h_t^2) data prior to that. For another part of the empirical work, the sample covers 1976-2013 and the 1976 start is due to the availability of credible monthly CPS data, from which the gross hiring flows (h_t^1) series is derived. This longer sample period covers five NBER-dated recessions, and both sample periods include the Great Recession (2007-2009) and its aftermath (2009-2013). The data include NIPA data on the NFCB GDP and its deflator, capital, investment, the price of investment goods and depreciation, BLS CPS data on employment and on worker flows, and Fed data computations on tax and depreciation allowances. Appendix C elaborates on the sources and on data construction. These data have the following distinctive features: (i) they pertain to the U.S. private sector; (ii) both hiring h_t and investment i_t refer to gross flows; likewise, separation of workers ψ_t and depreciation of capital δ_t are gross flows; (iii) the estimating equations take into account taxes and depreciation allowances. Table 7 presents key sample statistics.

Table 7

5.2 Estimation

I use the different model specifications discussed above. For the production function I use a standard Cobb-Douglas formulation, with productivity shock z_t :

$$f(z_t, n_t, k_t) = e^{z_t} n_t^\alpha k_t^{1-\alpha}, \quad 0 < \alpha < 1. \quad (21)$$

The costs function g was spelled out above (see equation (16)). Estimation pertains to the parameters $\alpha; e_1, e_2, e_{31}, e_{32}; \eta_1, \eta_2, \eta_{31}, \eta_{32}, \lambda_1, \lambda_2$, or to a sub-set of these parameters.

Estimation of the parameters in the production and costs functions allows for the quantification of the derivatives g_{i_t} and g_{v_t} that appear in the firms' optimality equations. I structurally estimate the firms' first-order conditions – equation (15) and the as-

sociated equation (14) – using Hansen’s (1982) generalized method of moments (GMM). The moment conditions estimated are those obtained under rational expectations. I report the J-statistic test of the over-identifying restrictions. I formulate the equations in stationary terms by dividing the investment equation by $\frac{f_t}{k_t}$ and the vacancy/hiring equation by $\frac{f_t}{n_t}$. Appendix B spells out the first derivatives included in these equations and the estimating equations. Importantly, I check whether the estimated g function fulfills the convexity requirement.

Note that the ideal case would be unconstrained estimation of the power parameters $\eta_1, \eta_2, \eta_{31}, \eta_{32}$, of the scale parameters e_1, e_2, e_{31} and e_{32} , and of the weights included in the second term, capturing recruiting, λ_1 and λ_2 . Attempting to do that, the estimation procedure did not converge. Hence constraints were imposed, and four parameters were freely estimated. Yashiv (2016) tried various configurations of $\eta_1, \eta_2, \eta_{31}, \eta_{32}$ estimation and reported the best ones. Following the results – see Table 2 (page 196) – the powers were set at $\eta_1 = \eta_2 = 2$ and $\eta_{31} = \eta_{32} = 1$. Note that placing such constraints on the powers is quite prevalent; often quadratic costs and linear interactions are simply assumed. The scale parameters (e_1, e_2, e_{31}, e_{32}) were freely estimated and are reported in Table 8 below. As to the parameters λ_1 and λ_2 , the following procedure was followed: (i) learning from past studies provided restrictions on the parameter space; and (ii) within this restricted space, fixed values were run and compared. I elaborate on each of these last two points in turn.

Regarding point (i), micro estimates using Swiss data reported in Blatter et al (2016, Table 1) and structural macro estimates using U.S. data in Furlanetto and Groshenny (2016, Table 3), Swedish data in Christiano, Trabandt, and Walentin (2011, p.2039), and Israeli data in Yashiv (2000, Table 2), show that vacancy posting costs are small compared to other components of hiring costs, particularly to training costs. Indeed, Christiano, Trabandt, and Walentin (2011), using Bayesian estimation of a DSGE model of Sweden, conclude, in this same context, that “employment adjustment costs are a function of hiring rates, not vacancy posting rates.” These studies then call for a low value of $1 - \lambda_1 - \lambda_2$. Following them, values of $0 \leq (1 - \lambda_1 - \lambda_2) \leq 0.3$ were examined.

As to point (ii), within the above restricted space, different values of λ_1 and λ_2 were tried. Empirical success was judged using the same criteria employed throughout: the J statistic test, convexity of the costs function (recalling that the second order conditions depend on the interaction terms), and getting cost estimates that are not large (see the discussion in Sub-section 6.1 below).

Using these two steps, the values of $\lambda_1 = 0.6$, $\lambda_2 = 0.2$ were obtained. A similar procedure yielded $\lambda = 0.9$ in the constrained case (row b of Table 8 below).

5.3 Post Estimation Approximation and Variance Decomposition

Post estimation I compute an approximated present value, Q_t^N and its variance decomposition. Iterating forward the RHS of (15) one gets:

$$PV_t = \sum_{j=1}^{\infty} \left[\begin{array}{c} \left(\prod_{l=1}^j \rho_{t+l} \frac{f_{t+l}}{n_{t+l}} \right) \left(\prod_{l=2}^j (1 - \psi_{t+l-1}) \right) (1 - \tau_{t+j}) \\ \left[\alpha - \frac{g_{t+j}}{f_{t+j}} - \frac{w_{t+j}}{n_{t+j}} \right] \end{array} \right] \quad (22)$$

Following Cochrane (1992), I use the following first-order Taylor expansion to get (see Appendices D and E for details⁷):

$$PV_t \cong E_t \left[\sum_{j=1}^{\infty} \exp \left[\sum_{l=1}^j g_{t+l}^r \right] \exp \left[\sum_{l=1}^j g_{t+l}^f \right] \exp \left[\sum_{m=l}^j g_{t+m-1}^s \right] MP_{t+j} \right] \quad (23)$$

where

$$MP_{t+j} \equiv (1 - \tau_{t+j}) \left(\alpha - \frac{g_{t+j}}{f_{t+j}} - \frac{w_{t+j}}{n_{t+j}} \right) \quad (24)$$

$$\begin{aligned} g_t^f &= \ln \left(\frac{f_{t+1}}{n_{t+1}} \frac{n_t}{f_t} \right) \\ g_t^s &\equiv \ln(1 - \psi_t) \\ g_t^r &\equiv \ln \rho_{t+1} \equiv \ln \left(\frac{1}{1 + r_t} \right) \end{aligned}$$

Using a sample period truncated at T , yields the variance decomposition:

⁷Note, though, that Cochrane (1992) does a second-order rather than a first-order Taylor expansion.

$$\begin{aligned}
var(PV_t) &\cong \frac{\Omega^r \Omega^f E(MP)}{1 - \Omega} \sum_{j=1}^T (\Omega)^{j-1} cov(PV_t, g_{t+j}^r) + & (25) \\
&\frac{\Omega^r \Omega^f E(MP)}{1 - \Omega} \sum_{j=1}^T (\Omega)^{j-1} cov(PV_t, g_{t+j}^f) + \\
&\frac{\Omega^r \Omega^f E(MP)}{1 - \Omega} \sum_{j=2}^T (\Omega)^{j-1} cov(PV_t, g_{t+j}^s) + \\
&\Omega^r \Omega^f \sum_{j=1}^T (\Omega)^{j-1} cov(PV_t, MP_{t+j})
\end{aligned}$$

where:

$$\begin{aligned}
\Omega^f &= e^{E(g_t^f)} \\
\Omega^s &= e^{E(g_t^s)} \\
\Omega^r &= e^{E(g_t^r)} \\
\Omega &= e^{E(w)} = \Omega^f \Omega^s \Omega^r \\
w_t &\equiv (g_t^f + g_t^s + g_t^r)
\end{aligned}$$

The variance of job values breaks down into terms relating to future discount rates (g_{t+j}^r), productivity growth (g_{t+j}^f), separation rates (g_{t+j}^s) and marginal profits (MP_{t+j}). In what follows I look at the relative size of the different terms on the RHS of equation (25) in order to gauge their relative importance.

6 Results

I present GMM estimates of equations (14) and (15) under the alternative specifications described above. Subsequently I use the estimates to present the variance decomposition defined in equation (25) and a graphical illustration of key relationships as implied by estimation.

I use three criteria to evaluate the estimates:

- a. The J-statistic test of the over-identifying restrictions.
- b. Fulfillment of the convexity requirement for the costs function g .
- c. The magnitude of implied total and marginal costs. As in many cases of invest-

ment equations estimated in the q-literature, some specifications imply very high costs. These are deemed to be unreasonable.

6.1 FOC Estimation

Table 8 reports the results of estimation. The table reports the point estimates and their standard errors, Hansen's (1982) J-statistic and its p-value, noting that some of the specifications estimated were also reported in Yashiv (2016). Table 9 shows the moments of the estimated marginal costs series.

Tables 8 and 9

Row (a) examines a quadratic function ($\eta_1 = \eta_2 = 2$) with linear interactions ($\eta_{31} = \eta_{32} = 1$).⁸ The weights on the different elements of the hiring process – vacancies, hiring from non-employment, and hiring from other employment – are expressed by the fixed parameters $\lambda_1 = 0.6, \lambda_2 = 0.2$, obtained after some experimentation. The parameters estimated are the scale parameters (e_1, e_2, e_{31} and e_{32}) of the frictions function (16) and the labor share (α) of the production function (21). The J-statistic has a high p-value, the parameters are precisely estimated, and the resulting g function fulfills all convexity requirements; the estimate of α is around the conventional estimate of 0.66. Table 9 indicates very moderate costs estimates.

Row (b) takes up a very similar specification but ignores job to job flows, i.e., sets $\lambda_2 = e_{32} = 0$ and $h_t^2 = \psi_t^2 = 0$. This allows for the use of a much longer data sample – 1976:1-2013:4, with 152 quarterly observations. It too yields a J-statistic with a high p-value, is, for the most part, precisely estimated, and the resulting g fulfills all convexity requirements.

The two rows – (a) and (b) - yield similar results in terms of the implied costs reported in Table 9. In particular, both feature negative coefficients for the interaction terms, implying complementarity between hiring and investment.

Row (c) follows standard Tobin's q type of models applied to the hiring of labor and looks at a quadratic specification, ignoring the other factor of production (here ignoring investment in capital). It thus sets $\eta_2 = 2, e_1 = e_{31} = e_{32} = 0$, i.e., has quadratic vacancy and hiring costs, with no role for capital (see equation (17)). While there is no rejection of the model, this specification implies very high, unreasonable costs, as seen in Table 9. This is reminiscent of the results in the literature on Tobin's q models for investment.

⁸See Yashiv (2016, section 4.3) for a discussion of other specifications.

Row (d) reports the results of the standard (Pissarides-type) search and matching model formulation with linear vacancy costs and no other arguments, as formulated in equation (18), such that $\eta_2 = 1, e_1 = e_{31} = e_{32} = \lambda_1 = \lambda_2 = 0$. The emerging estimates imply even higher costs (shown in Table 9) and the parameter α is estimated at a high value (0.77).

To see these results in context note the following findings. Mortensen and Nagypal (2006, page 30) note that “Although there is a consensus that hiring costs are important, there is no authoritative estimate of their magnitude. Still, it is reasonable to assume that in order to recoup hiring costs, the firm needs to employ a worker for at least two to three quarters. When wages are equal to their median level in the standard model ($w = 0.983$), hiring costs of this magnitude correspond to less than a week of wages.” The widely-cited Shimer (2005) paper calibrates these costs at $\frac{c}{q} = 0.16$ using a linear cost function, which is equivalent to 3.4 weeks of wages. Hagedorn and Manovskii (2008) decompose this cost into two components: (i) the capital flow cost of posting a vacancy; they compute it to be – in steady state – 47.4 percent of the average weekly labor productivity; (ii) the labor cost of hiring one worker, which, relying on micro-evidence, they compute to be 3 percent to 4.5 percent of quarterly wages of a new hire. The first component would correspond to a figure of 0.037 here; the second component would correspond to a range of 0.02 to 0.03 in the terms used here; together this implies 0.057 to 0.067 in current terms or around 1.1 to 1.3 weeks of wages. Blatter et al (2016) survey the micro literature and report estimates of hiring costs ranging between 25% and 131% of quarterly wages, i.e. between 3.25 and 17 weeks of wages.

The estimates for the preferred specification, i.e., the GMM results reported in row (a) of Table 8 and the first column of Table 9, pertain to marginal costs with a convex costs function, while most of the above pertain to average costs, usually with a linear function. The preferred specification here has an estimate of $(1 - \tau_t) \frac{g_{v,t}}{q_t \frac{f_t}{n_t}}$ which is 0.12 at its sample average; given that $\frac{w_t}{\frac{f_t}{n_t}} = 0.62$ on average, this is the equivalent of 2.5 weeks of wages. In light of the cited numbers, this is at the low end of the range of macro and micro estimates. The Tobin-q model and the standard model yield the equivalent of 19 and 20 weeks of wages, which are far above the estimates in the literature.

The estimates of marginal investment costs, implied by the preferred specification of row (a) in Table 8, are on average $\frac{g_{i,t}}{\frac{f_t}{k_t}} = 0.53$. This estimate is equivalent to an addition of 3% to the price of a unit of capital. In other words, for every dollar spent on the marginal unit of capital purchased, the firm adds 3 cents in adjustment costs. This result can be compared to the q-literature. One can divide the results in this literature

into three sets: (i) the earlier studies, from the 1980s, suggested high costs, whereby marginal costs range between 3 to 60 in the above terms (average output per unit of capital) and the implied total costs range between 15% to 100% of output; (ii) more recent studies which have reported moderate costs, whereby marginal costs are around 1 in the same terms of average output per unit of capital, and total costs range between 0.5% to 6% of output; (iii) micro-based studies, using cross-sectional or panel data, which have reported low costs, with marginal costs at 0.04 to 0.50 of average output per unit of capital and total costs range between 0.1% to 0.2% of output. The current results are at the high end of the third, low-costs set.

In what follows I denote the results of row (a) as the preferred specification, noting that row (b) yields a similar picture over a longer sample period. I focus on row (a) so as to continue to take into account job to job flows, available only from 1994.

6.2 Post Estimation: Approximation and Variance Decomposition

Table 10 reports the results of the variance decomposition defined by equation (25) following the approximation equation (23).⁹

Table 10

For the preferred specification, Table 10 shows that the key determinant of job value volatility (denoted $var(PV_t)$) is the last term, i.e., the sum of the co-variances of job values with future marginal profits $\sum_{j=1}^T (\Omega)^{j-1} cov(PV_t, MP_{t+j})$. Recall that marginal profits

MP_{t+j} are net marginal productivity less the wage, i.e., $(1 - \tau_{t+j}) \left(\alpha - \frac{g_{t+j}}{f_{t+j}} - \frac{w_{t+j}}{n_{t+j}} \right)$.

With the small variability of τ_{t+j} and $\frac{g_{t+j}}{f_{t+j}}$, the main driver of volatility are the future labor shares $\frac{w_{t+j}}{n_{t+j}}$. All other terms in the decomposition play a very small role.

For the Tobin'q specification and for the standard search and matching model, Table 10 shows that there is some role in the variance decomposition also for the discount rate, the productivity growth rate and the separation rate. Together they account for about 20% of the variance of the approximated, truncated present value, as compared to less than 2% in the preferred specification. This difference helps explain some further implications of the estimates, discussed below.

⁹Experimentation with different values for the truncated horizon shows that starting with $T = 30$ there is almost no change in the resulting PV (but as T rises the series is shortened). Hence the latter value was chosen to be reported.

6.3 Implications for Key Relationships

I look at the implications of the preferred specification for key relationships in the model. One such relationship is that of vacancy rates ($\frac{v_t}{n_t}$) with job values ($\frac{Q_t^N}{\frac{I_t}{n_t}}$) and investment rates ($\frac{i_t}{k_t}$). Using equation (12) and the estimates of row (a) in Table 8 this is given by:

$$\frac{v_t}{n_t} = \frac{\frac{Q_t^N}{\frac{I_t}{n_t}}(q_t^1 + q_t^2)}{(1 - \tau_t)} - (e_{31}q_t^1 + e_{32}q_t^2) \frac{i_t}{k_t} \quad (26)$$

This equation is plotted in Figure 6.¹⁰

Figure 6

This is a linear relationship, whereby labor recruiting, as expressed by the vacancy rate, rises with job values and with the other firm activity – the capital investment rate. In the following sections I look at the cyclical behavior and volatility of these three key variables – $\frac{v_t}{n_t}$, $\frac{Q_t^N}{\frac{I_t}{n_t}}$ and $\frac{i_t}{k_t}$.

Another such relationship is the one between vacancy rates ($\frac{v_t}{n_t}$) and the job filling rates (q_t^1, q_t^2) which the firm faces. These job-filling rates express the influence of matching processes and market conditions, taken as given by the firm. This is shown in Figure 7.¹¹

Figure 7

This is a non-linear relationship. The figure shows a non-trivial asymmetry: recruiting ($\frac{v_t}{n_t}$) *falls* as the job filling rate from non-employment (q_t^1) rises, and *rises* as the job filling rate from other firms (q_t^2) rises. Why so? Each job filling rate has three effects. One is to increase the job value,¹² thereby increasing the vacancy rate. A second is to

¹⁰The figure uses the sample averages of tax rates (τ_t) and job filling rates (q_t^1, q_t^2) and employs the point estimates of the preferred specification. The figure uses empirically-relevant ranges for $\frac{v_t}{n_t}$, shown on the vertical axis, and $\frac{Q_t^N}{\frac{I_t}{n_t}}$ and $\frac{i_t}{k_t}$, shown on the horizontal axes.

¹¹The figure uses equation (26), the estimates of row (a) in Table 8, and the sample averages of τ_t , $\frac{Q_t^N}{\frac{I_t}{n_t}}$ and $\frac{i_t}{k_t}$.

¹²Referring to the term $\frac{Q_t^N}{\frac{I_t}{n_t}}(q_t^1 + q_t^2)$.

reduce marginal costs via the interaction with the rate of investment,¹³ which also operates to increase the vacancy rate. The third is a scale effect that raises marginal costs for any given level of the vacancy rate.¹⁴ This third effect operates to lower the vacancy rate. The estimation results of the preferred specification imply that the third effect dominates in the case of the job filling rate from non-employment (q_t^1) and that the first two effects dominate in the case of the job filling rate from other firms (q_t^2).

7 The Cyclicity of Job Values

Section 5 above has presented the cyclical properties of the key *data* series. This section examines the cyclical properties of *estimated* job values in the different models.

Table 11 reports the cyclical behavior of estimated job values, using the point estimates of the LHS of equation (15), i.e., of marginal hiring costs, as reported in the different specifications of Table 8. Figure 8 presents the time series plots of these marginal costs (with the left scale measuring the benchmark and constrained models and the right scale the other two models).

Table 11 and Figure 8

The preferred specification (row (a) of Table 8) indicates counter-cyclicity, the constrained specification (row (b) of Table 8) weak counter-cyclicity, the Tobin's q model is weakly pro-cyclical (row (c) of Table 8), while the standard model (row (d) of Table 8) is strongly pro-cyclical.

Getting back to equation (1) the implications of these results are that they indicate very different views of the cyclicity of job values.

Starting with the specification of row (d) in Table 8, the standard search and matching (Pissarides-type) model, note that in its simple form the optimality equation is given by (re-writing equation (18)):

$$(1 - \tau_t) \frac{e_2}{q_t} = E_t \left[\rho_{t+1} (1 - \tau_{t+1}) \frac{1}{\frac{f_t}{n_t}} \left[f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} + (1 - \psi_{t+1}) \frac{e_2}{q_{t+1}} \frac{f_{t+1}}{n_{t+1}} \right] \right] \quad (27)$$

This equation has a pro-cyclical MC_t on the LHS, as shown in Table 11 and Figure 8. This is to be expected as it depends inversely on the matching rate $q_t = \frac{h_t}{v_t}$, which itself

¹³Referring to the term $-(e_{31}q_t^1 + e_{32}q_t^2) \frac{h_t}{k_t}$, noting that $e_{31}, e_{32} < 0$.

¹⁴Referring to the term $e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2$

is highly counter-cyclical.

The specification of row (c) in Table 8, the Lucas-Prescott/Tobin approach has marginal costs being weakly pro-cyclical, as seen in Table 11 and Figure 8. Repeating equation (17):

$$(1 - \tau_t) \frac{e_2}{q_t} \left[\begin{array}{c} (1 - \lambda_1 - \lambda_2) \\ + \lambda_1 q_t^1 + \lambda_2 q_t^2 \end{array} \right]^2 \frac{v_t}{n_t} = E_t \frac{1}{\frac{f_t}{n_t}} \left[\rho_{t+1} (1 - \tau_{t+1}) \left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ + (1 - \psi_{t+1}) \frac{g_{v_{t+1}}}{q_{t+1}} \end{array} \right] \right] \quad (28)$$

The reason for the weak pro-cyclicality is that the pro-cyclicality of $\frac{e_2}{q_t}$ and of $\frac{v_t}{n_t}$ is offset to some extent by the counter-cyclicality of q_t^1 and q_t^2 .

The preferred specification of row (a) in Table 8, implies the opposite. The results of Table 11 and Figure 8 indicate counter-cyclicality. Note that this is a broader model. It follows the Pissarides approach of using a vacancy creation equation but MC_t depends on all the relevant rates $-\frac{h_t^1}{n_t}, \frac{h_t^2}{n_t}$ and $\frac{v_t}{n_t}$. The equation here is:

$$(1 - \tau_t) \frac{1}{q_t} \left[\begin{array}{c} e_2 \left[\begin{array}{c} (1 - \lambda_1 - \lambda_2) \\ + \lambda_1 q_t^1 + \lambda_2 q_t^2 \end{array} \right]^2 \frac{v_t}{n_t} \\ + (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t} \end{array} \right] = E_t \frac{1}{\frac{f_t}{n_t}} \left[\rho_{t+1} (1 - \tau_{t+1}) \left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ + (1 - \psi_{t+1}) \frac{g_{v_{t+1}}}{q_{t+1}} \end{array} \right] \right] \quad (29)$$

This model delivers counter-cyclicality on both sides of the equation, as the pro-cyclicality of $\frac{1}{q_t} \frac{v_t}{n_t}$, and of $(e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}$ is out-weighed by the counter-cyclical term $[(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2$.

Note, two related points:

One is that it is of course not only the LHS of the hiring optimality equation which differ across models, but also their RHS. In equations (27), (28) and (29) above, the expressions $\frac{g_{v_{t+1}}}{q_{t+1}}$ differ across models. Note that Table 10 gave evidence of that in terms of the variance decomposition.

The second is that all three models relate to the present value of marginal profits. One can therefore ask what is the cyclical behavior of this latter present value, and why do the models differ on this aspect. I examine this question in the next section.

In a recent paper, Kudlyak (2014) suggested a related concept she has termed "the user cost" of labor. Comparing this concept to the current one, the following can be shown. The user cost of labor is the sum of two terms:

- (i) the first difference in job values, $\frac{Q_t^N}{\frac{f_t}{n_t}}$, with proper discounting, what Kudlyak

(2014, equation 4) calls UC_t^V .

(ii) a term that Kudlyak (2014, equation 2) calls UC_t^W and defines as (p.56): “the sum of the hiring wage in period t and the expected present value of the differences between wages paid from the next period onward in the employment relationship that starts in t and the employment relationship that starts in $t + 1$.”

Hence the job value is not the user cost of labor. Two crucial differences emerge between Kudlyak (2014) and this paper:

a. The user cost UC_t is not the same concept as the job value and not even of its first difference, as it includes an important other component, UC_t^W .

b. Kudlyak (2014) assumes constant discounting, constant separation, no productivity growth, no taxes, and no employment-dependent hiring costs.

This leads to the following key differences in the analysis:

a. The cyclicity of UC_t should not be expected to be the same as the cyclicity of $\frac{Q_t^N}{\frac{f_t}{n_t}}$, which is a key issue in the current paper.

b. The analysis of this paper assigns a role to variable discounting, separation and productivity growth; Table 10 column 4 assigns 16% of the variance of the relevant present value expression – within the framework of the standard search and matching model – to those variables which are assumed constant in Kudlyak (2014).

Moreover, the above holds true for the restricted setting of the standard search and matching model cost function which has $e_1 = e_{31} = e_{32} = 0, \lambda_1 = \lambda_2 = 0$ and $\eta_2 = 1$. The main parts of the current paper deal with the preferred specification of hiring costs, which are richer.

8 The Role of the Labor Share in Job Value Cyclicity

The labor share in GDP plays a key role in the afore-going results. It has also been the focus of some attention in recent macroeconomic models of the business cycle. The main reason for the key results of this paper is its cyclical behavior. The variance decomposition of the approximated PV_t , reported in Table 10 above, has shown that the key role is played by marginal profits (repeating equation (24)):

$$MP_{t+j} \equiv (1 - \tau_{t+j}) \left(\alpha - \frac{g_{t+j}}{\frac{f_{t+j}}{n_{t+j}}} - \frac{w_{t+j}}{\frac{f_{t+j}}{n_{t+j}}} \right) \quad (30)$$

As α is constant, the tax rate (τ_{t+j}) is fixed over long periods and the term $\frac{-g_{t+1}}{\frac{f_{t+1}}{n_{t+1}}}$ is

estimated to be small, the main driver is the labor share, $\frac{w_{t+1}}{\frac{f_{t+1}}{n_{t+1}}}$.

Consider the cyclical behavior of the labor share. In Table 12, I present in panel (a) its dynamic correlations with GDP. In panel (b), I present the dynamic correlations with GDP of an approximated present value of these marginal profits (30), given by:¹⁵

$$PV_t(MP_{t+s}) = \sum_{s=1}^T \left(\frac{1}{(1-\psi_t)} \prod_{i=1}^s \rho_{t+i} \frac{\frac{f_{t+i}}{n_{t+i}}}{\frac{f_{t+i-1}}{n_{t+i-1}}} (1-\psi_{t+i-1}) \right) (1-\tau_{t+s}) \left[\alpha - \frac{w_{t+s}}{\frac{f_{t+s}}{n_{t+s}}} \right]. \quad (31)$$

Note that these dynamic correlations, for logged and HP filtered variables, are computed using only data, with no parameter estimates.

Table 12

Noting the bolded numbers in panel (a) of the table, dynamically, the labor share is pro-cyclical. As a result the job values it engenders are counter-cyclical. This counter-cyclical behavior can be seen in panel (b), showing the dynamic correlations of the approximated job value expression in (31) with GDP. It is this dynamic stochastic behavior of the labor share which is the key determinant of counter-cyclical job values.

Note that the different models examined in estimation capture this job value behavior differentially, as seen in Section 7 above. There are several reasons for the differences across models: the relevant estimating equations, i.e., the empirical counterparts of equations (27), (28) and (29), use data from adjacent periods t and $t+1$ rather than T period ahead data as in equation (31); the empirical equations use actual data variables, not expected ones, and thus contain errors; and the models posit different parametric forms of the cost function (g) and hence constrain the empirical equations in different ways.

The point is that the preferred specification captures the counter-cyclical behavior of job values shown in Table 12, while the Tobin and standard search and matching models do not.

This cyclical behavior of the labor share has recently been noted by a number of authors in other Macro contexts. The observation, whereby the labor share first falls in a boom and subsequently rises for a substantial period of time, i.e., is dynamically pro-cyclical, was discussed by Rios-Rull and Santaella-Llopis (2010). Hall (2014) finds

¹⁵There are two aspects to this approximation: it ignores the $\frac{g_{t+1}}{\frac{f_{t+1}}{n_{t+1}}}$ term and it truncates the infinite sum at T .

that the labor share is a-cyclical contemporaneously and pro-cyclical subsequently. Nekarda and Ramey (2013) examine the cyclicity of mark-ups. Essentially they treat the mark-up as the inverse of the labor share (see their equation 5), allowing various modifications to the relationship, such as overhead hours, CES production functions, and differentials between marginal and average wages. Studying both aggregate and four-digit manufacturing data of the U.S. economy, they find that mark-ups are *contemporaneously* pro-cyclical and that *dynamically* they are counter-cyclical. The latter finding means that if GDP is low now (recession), mark-ups will rise henceforth (see their Figure 2). This is similar to the finding here that job values are counter-cyclical, i.e., that the *present value* of profits rises in recessions. It is so for the same reason, namely that the future labor share declines (i.e., again, dynamically the labor share is pro-cyclical). These findings are not in contradiction with the findings of other recent papers, such as Haefke, Sonntag, and van Rens (2013), whereby the real wage w_t itself is contemporaneously and over some lags and leads pro-cyclical, as this is true for the current paper's data.

Note that the current paper does not discuss a general equilibrium, structural model. It focuses only on the FOC for firm optimal hiring and investment. Inter alia, it takes wage share behavior as given. Therefore it does not attempt to explain the reasons for the dynamic pro-cyclicity of the labor share. But such an explanation may be derived from a structural DSGE setting. Thus, Rios-Rull and Santaaulalia-Llopi (2010) point out that in RBC modelling, in order to account for this pattern of the data, one cannot maintain the assumptions of Cobb Douglas production and competitive factor prices. They point to labor search models as a potential modelling route. In those models, a bargaining protocol for wages, combined with the FOC of the type examined here, breaks the identity of wage and labor productivity behavior. In this set up, following a positive productivity shock, the model may replicate the data: wages rise a bit and then fall slowly, while the average product rises a lot and then monotonically declines; consequently, the labor share first drops and then rises (see their Figure 6 on page 946). A different modelling direction was proposed by Growiec, McAdam and Mućkr (2015). They find that in the medium-term the labor share is pro-cyclical, while in the short run it is counter-cyclical. These findings are in line with the current findings. They then offer explanations in terms of an endogenous, R&D-based growth model, with capital and labor augmenting innovations.

Note, too, that the different models examined in estimation capture this job value behavior differentially, as seen in Section 7 above. There are several reasons for the differences across models: the relevant estimating equations, i.e., the empirical counterparts of the FOC equations of the three models use data from adjacent periods t and

$t + 1$ rather than T period ahead data as in equation (22); the empirical equations use actual data variables, not expected ones, and thus contain errors; and the models posit different parametric forms of the cost function (g) and hence constrain the empirical equations in different ways. It is this last point which deserves emphasis. The standard model places the following restrictions: $e_1 = e_{31} = e_{32} = 0, \lambda_1 = \lambda_2 = 0$ and $\eta_2 = 1$. Tobin's Q model places the restrictions $e_1 = e_{31} = e_{32} = 0$ and $\eta_2 = 2$. It turns out that the data do not conform these restrictions. The preferred specification, which gives differential weights to the different recruiting variables (unlike the standard model), and allows for important interactions with investment (unlike the standard model and Tobin's model), fits the data better. It delivers a "different story," whereby hiring and job values are counter-cyclical, while the Tobin and standard search and matching models do not, as shown in Table 11.

9 The Volatility of Recruitment Rates

The focus so far has been on the cyclical nature of recruiting and of the associated job values. In this section I turn to study the *volatility* of the key variables expressing recruitment behavior, using the estimation results. In particular, I seek to explain the finding of high volatility, which has been widely discussed in the literature, mostly following Shimer (2005). The idea is to show that the estimated model not only explains co-movement but is able also to account for high volatility. The connections of co-movement and volatility are then explored.

I start by presenting some pertinent data moments. I then do variance decompositions of the vacancy rate, the total hiring rate, and the rate of hiring from non-employment using the preferred estimates. I conclude by summarizing the findings with respect to the determinants of the high volatility of these recruitment variables.

9.1 Data Moments

To fix ideas as to the volatility facts to be explained in this section, consider the following data moments. Table 13a shows the volatility, in terms of the standard deviations, of the key variables in firm behavior: the hiring rate – both the total one $\frac{h_t}{n_t}$ and the rate from non-employment $\frac{h_t^1}{n_t}$, the vacancy rate $\frac{v_t}{n_t}$, and the job filling rates q_t^1 and q_t^2 . I also look at the investment rate $\frac{i_t}{k_t}$.¹⁶ Table 13b presents the standard deviation and corre-

¹⁶The discussion here complements the discussion in Section 4 above. All variables are logged and HP-filtered.

lation of two key determinants: output (NFCB GDP, f_t) and the job value $(\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}})$, as estimated in Table 8 row (a). Table 13c reports the co-movement of the firm variables of Table 13a and the two determinant variables examined in Table 13b.

Tables 13 a,b,c

These series are all shown in Figure 9 with the vertical lines indicating the start and end of NBER-dated recessions.

Figure 9

The following points may be noted:

(i) The vacancy rate and the job filling rates are highly volatile. This a key point to be explained.

(ii) The above rates are much more volatile than the hiring rates. Why so? Noting that $\frac{h_t}{n_t} = (q_t^1 + q_t^2)\frac{v_t}{n_t}$, this is the result of the negative co-movement of vacancy rates $\frac{v_t}{n_t}$ and job filling rates $(q_t^1 + q_t^2)$.

(iii) Job values are much more volatile than output and are negatively correlated with it, i.e., are countercyclical. The latter feature was emphasized above. In what follows we shall see how this stochastic behavior accounts for volatility.

(iv) In terms of business cycle facts, the well-known moments shown here are the pro-cyclicality of the investment rate and of the vacancy rate and the counter-cyclicality of job filling rates. Much less known is the weak cyclicality of hiring rates, with the rate of hiring from non-employment, actually being counter-cyclical, as discussed in Section 4 above.

(v) Job values have positive co-movement with the worker flow from non-employment, as expressed by the hiring rate $\frac{h_t^1}{n_t}$ and the job filling rate q_t^1 . But they negatively co-move with the decision variables of the firm – vacancy and investment rates. This feature, too, plays a role in explaining volatility.

These moments suggest differential behavior of the various recruitment variables, which I turn to analyze using variance decompositions.

9.2 The Vacancy Rate

As the analysis is somewhat involved, I break it down into sub-topics.

Deriving The Vacancy Rate in the Estimated Model. To explain the volatility of the vacancy rate, I start off from the F.O.C:

$$(1 - \tau_t) \frac{g_{v_t}}{q_t \frac{f_t}{n_t}} = \frac{Q_t^N}{\frac{f_t}{n_t}}$$

Using the preferred estimates of Table 8 row (a) I get:

$$\frac{1}{q_t^1 + q_t^2} \left[e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2 \frac{v_t}{n_t} + (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t} \right] = \frac{Q_t^N}{(1 - \tau_t) \frac{f_t}{n_t}}$$

The vacancy rate can then be expressed as follows (basically re-writing equation (26)):

$$\frac{v_t}{n_t} = \frac{\frac{Q_t^N}{(1 - \tau_t) \frac{f_t}{n_t}} (q_t^1 + q_t^2)}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2 - \frac{(e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}} \quad (32)$$

Equation (32) shows that the vacancy rate is composed of two terms:

- (i) The job value $\frac{Q_t^N}{(1 - \tau_t) \frac{f_t}{n_t}}$, multiplied by a factor $\left(\frac{(q_t^1 + q_t^2)}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2} \right)$, which is a non-linear function of the job filling rates q_t^1 and q_t^2 and model parameters $(e_2, \lambda_1, \lambda_2)$.
- (ii) The investment rate $\frac{i_t}{k_t}$, multiplied by another factor $\left(\frac{-(e_{31} q_t^1 + e_{32} q_t^2)}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2} \right)$, which is a (different) non-linear function of the job filling rates q_t^1 and q_t^2 and model parameters $(e_2, e_{31}, e_{32}, \lambda_1, \lambda_2)$.

In other words, vacancy rates are driven by job values, and through the interaction of costs, by investment rates, themselves driven by capital values.

Variance Decomposition of the Vacancy Rate. Table 14 reports the following variance decomposition which ensues from equation (32):

$$\begin{aligned}
\text{var}\left(\frac{v_t}{n_t}\right) = & \text{var}\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1 + q_t^2)}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \\
& + \text{var}\left(\frac{(e_{31}q_t^1 + e_{32}q_t^2)\frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \\
& - 2\text{cov}\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1 + q_t^2)}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}, \frac{(e_{31}q_t^1 + e_{32}q_t^2)\frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right)
\end{aligned} \tag{33}$$

Table 14

The table implies that by far the biggest part of the variance of vacancy rates can be attributed to its second term, i.e., to investment rates $\frac{i_t}{k_t}$ multiplied by the factor delineated above. Note that this term becomes zero in the case of no interaction of hiring costs and investment costs ($e_{31} = e_{32} = 0$).

The Co-Movement of the Constituents of the Vacancy Rate. In order to better understand the significance of this breakdown, Table 15 shows correlations of these two terms, the constituents of vacancy rates, with GDP (f_t) and with job values ($\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$), where all variables have been logged and HP-filtered:

Table 15

Vacancy rates are pro-cyclical (0.91) and are negatively correlated (-0.56) with job values. This pro-cyclicity, as well as the negative correlation with job values, is very much engendered by the correlations of *the second term*, the investment rate multiplied by a factor, with GDP and with job values. In contrast, the first term determining the vacancy rate, job values multiplied by a factor, is weakly pro-cyclical and has a positive, rather than negative, correlation with job values.

The Determinants of High Vacancy Volatility. The second moments of the vacancy rate are dominated by the interaction of hiring and investment costs. Note that investment rates themselves are volatile and pro-cyclical, as reported in Tables 13 a and c above.

It is this vacancy rate which has been, together with the unemployment rate, at the center of attention in the discussions of high labor market volatility following Shimer (2005). The analysis here points to a volatility determinant which has received little, if

any, attention previously: the capital investment rate, operating through the interaction of investment and hiring costs.

I turn now to study the other two recruiting variables, total hiring and hiring from non-employment, using a similar analysis.

9.3 The Total Hiring Rate

I analyze the behavior of the hiring rate in the same way. Note that the total hiring rate $\frac{h_t}{n_t}$ is given by:

$$\begin{aligned} \frac{h_t}{n_t} &= (q_t^1 + q_t^2) \frac{v_t}{n_t} = \frac{\frac{Q_t^N}{(1-\tau_t) \frac{i_t}{n_t}} (q_t^1 + q_t^2)^2}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2} \\ &\quad - \frac{(q_t^1 + q_t^2) (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2} \end{aligned} \quad (34)$$

I repeat the same computations for hiring rates. The variance of hiring rate is given by:

$$\begin{aligned} \text{var}\left(\frac{h_t}{n_t}\right) &= \text{var}\left(\frac{\frac{Q_t^N}{(1-\tau_t) \frac{i_t}{n_t}} (q_t^1 + q_t^2)^2}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \\ &\quad + \text{var}\left(\frac{(q_t^1 + q_t^2) (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \\ &\quad - 2\text{cov}\left(\frac{\frac{Q_t^N}{(1-\tau_t) \frac{i_t}{n_t}} (q_t^1 + q_t^2)^2}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}, \frac{(q_t^1 + q_t^2) (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \end{aligned} \quad (35)$$

This yields the following decomposition in Table 16:

Table 16

The table implies that by far the bigger part of the variance of hiring rates can again be attributed to its second term, i.e., investment rates $\frac{i_t}{k_t}$ multiplied by a factor.¹⁷This

¹⁷The factor is given by $\frac{(q_t^1 + q_t^2)(e_{31} q_t^1 + e_{32} q_t^2)}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}$, a non-linear function of the job filling rates q_t^1 and q_t^2 and model parameters $(e_2, e_{31}, e_{32}, \lambda_1, \lambda_2)$.

term, again, is zero in the case of no interaction of hiring costs and investment costs ($e_{31} = e_{32} = 0$).

Table 17 shows the correlations of the two components of $\frac{h_t}{n_t}$ with GDP (f_t) and with job values ($\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$), where all variables have been logged and HP-filtered:

Table 17

In this case hiring is just weakly related to GDP and to job values. Its two constituent terms offset each other, hence the weak correlations.

9.4 The Rate of Hiring from Non-Employment

Turning now to a sub-set of total hiring, the hiring rate from non-employment, it is given by:

$$\frac{h_t^1}{n_t} = q_t^1 \frac{v_t}{n_t} = \frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} (q_t^1 + q_t^2) q_t^1}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2} - \frac{q_t^1 (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2} \quad (36)$$

Thus:

$$\begin{aligned} \text{var}\left(\frac{h_t^1}{n_t}\right) &= \text{var}\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} (q_t^1 + q_t^2) q_t^1}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \\ &+ \text{var}\left(\frac{q_t^1 (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \\ &- 2\text{cov}\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}} (q_t^1 + q_t^2) q_t^1}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}, \frac{q_t^1 (e_{31} q_t^1 + e_{32} q_t^2) \frac{i_t}{k_t}}{e_2 [(1 - \lambda_1 - \lambda_2) + \lambda_1 q_t^1 + \lambda_2 q_t^2]^2}\right) \end{aligned} \quad (37)$$

This yields the following decomposition in Table 18:

Table 18

Here it is *the first term*, which depends on the job value, which plays the bigger role.

Table 19 shows the correlations of the two components of $\frac{h_t^1}{n_t}$ with GDP (f_t) and with job values ($\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$), where all variables have been logged and HP-filtered:

Table 19

The dominant role of the job value term is seen here by the correlation of the hiring rate ($\frac{h_t^1}{n_t}$) with it, 0.78, and by the fact that the hiring rate is counter-cyclical, following the counter-cyclical of job values.

Note that the results of Tables 18 and 19, where job values dominate, are almost the opposite of the results of Tables 14 and 15 with respect to the vacancy rate and the results of Tables 16 and 17 with respect to the total hiring rate, where the interaction with investment rates dominates.

9.5 Summing Up

The key series pertaining to worker recruiting display substantially different behavior.

(i) For both the vacancy rate $\frac{v_t}{n_t}$ and the total hiring rate $\frac{h_t}{n_t}$ the following is found:

a. There are two determinants: the job value $\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$ multiplied by a factor, and the investment rate $\frac{i_t}{k_t}$ multiplied by a different factor, with each factor being a function of the job filling rates and model parameters. These factors are functions of market conditions.

b. Much of the variance comes from the term which depends on the investment rate, hence the interaction of hiring costs and investment costs is key.

c. Both are pro-cyclical due to the fact that the high pro-cyclical of the investment rate term dominates the counter-cyclical of the job value term.

(ii) The hiring rate from non-employment $\frac{h_t^1}{n_t}$ behaves differently, almost the opposite of the afore-going, and is counter-cyclical. It follows the behavior of job values, as the $\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$ term dominates.

Hence the volatility of vacancy and total hiring rates is driven by capital investment behavior, while that of hiring from non-employment by the (different) behavior of job values.

It is important to note that these conclusions point to two variables that got little attention in the literature:

a. The job value, which is a present value, forward-looking variable that depends on both productivity and wages; the literature tended to focus on the role of current

productivity and the response of current wages to it.

b. The capital value, affecting volatility via the interaction of investment and hiring costs, and coming into play via the investment rate term.

10 Explaining the Decline in Labor Market Fluidity

Recently, Davis and Haltiwanger (2014) have documented a decline over time in U.S. labor market fluidity. They provide detailed evidence, in terms of both worker flows and job flows (see, in particular, their Figures 1-10). In terms of the variables in the current data set, this is manifested in the decline of $\frac{h^1}{n}$, $\frac{h^2}{n}$, ψ^1 , ψ^2 and $\frac{v}{n}$, which can be seen in Figure 10 for the full sample period (noting that job to job flows are measured from 1994 only). The figure shows the raw data, not detrended.

Figure 10

The afore-going analysis can account for these facts too. Consider the following equation derived from equation (12):

$$\frac{Q_t^N}{\frac{f_t}{n_t}} = (1 - \tau_t) \frac{g v_t}{q_t^1 \frac{f_t}{n_t}} \quad (38)$$

Table 20 shows the estimated LHS and the RHS of equation (38) separately for two sub-periods. As it is hard to pinpoint one particular year as the dividing line, somewhat arbitrarily the following sub-periods were examined: 1976-1995 and 1996-2013. In order to cater for the longest sample period possible, the figure uses the preferred estimates of row (b) in Table 8. It uses point estimates for the parameter values and the estimated average job value $\frac{Q_t^N}{\frac{f_t}{n_t}}$ in each sub-sample. It also uses the data averages in the sub-samples for the variables τ_t , q_t^1 and $\frac{i_t}{k_t}$. Note that under this specification, which omits job to job flows, the RHS of equation (38) is given by (omitting time sub-scripts to denote averages):

$$\begin{aligned} (1 - \tau) \frac{g v}{q^1 \frac{f}{n}} &= \frac{(1 - \tau)}{q^1} \left(e_2 \left(1 - \lambda_1 + \lambda_1 q^1 \right)^2 \frac{v}{n} + e_3 q^1 \frac{i}{k} \right) \\ &= (1 - \tau) e_3 \frac{i}{k} + \frac{(1 - \tau)}{q^1} e_2 \left(1 - \lambda_1 + \lambda_1 q^1 \right)^2 \frac{v}{n} \end{aligned} \quad (39)$$

Table 20

Figure 11 plots the LHS and RHS of equation (39) in the space of MC and PV on the vertical axis and vacancy rates $\frac{v}{n}$ on the horizontal axis.

Figure 11

The table and the figure show that job values ($\frac{Q_t^N}{L_t^n}$) – depicted as the horizontal lines in the figure – declined somewhat going from the pre-1995 period to the post-1995 period. The upward sloping curve, expressing marginal costs ($(1 - \tau) \frac{s_v}{q_t^1 \frac{L_t^n}{n}}$), moved in a counter-clockwise fashion. The changes in this latter curve are as follows: its intercept $(1 - \tau_t) e_3 \frac{i_t}{k_t}$ declined as the tax rate fell and the investment rate increased, noting that $e_3 < 0$; its slope $\frac{(1 - \tau_t)}{q_t^1} e_2 (1 - \lambda_1 + \lambda_1 q_t^1)^2$ went up with the rise in q_t^1 and the fall in the tax rate. The final outcome, shown in the intersection of the dashed lines marked ‘new’ as compared to the ‘old’ intersection, was that vacancy rates declined.

This analysis implies that the outcome of a lower vacancy rate, i.e., a decline in recruiting activity, took place as the result of the rise in the investment rate, the fall in the tax rate, and the rise in the job filling rate, all of which led to a movement of the marginal costs curve in a counter-clockwise direction. In other words, vacancy rates declined as job values went down and as the marginal cost curve became steeper.

11 Conclusions

The paper has provided a consistent picture of firm recruiting behavior in the U.S. First, job values were found to be counter-cyclical, mainly because of labor share cyclical-ity. The analysis has emphasized their forward-looking, present value aspect. Second, and as a consequence, hiring from non-employment and the associated job-filling rate are counter-cyclical. This behavior is consistent with known facts in the labor market. These two points are different, though, from the conclusions of the standard search and matching model. Third, the same framework can account for the pro-cyclicality of vacancy rates and job to job flows; these stem from the important interaction of labor recruiting behavior with capital investment behavior. Fourth, both the high volatility of key recruiting variables at business cycle frequency and their declining secular trends can be accounted for, using the same framework.

The paper has undertaken a partial equilibrium analysis. This type of analysis enables it to avoid mis-specifications and empirical difficulties in other parts of the macro-economy when studying the above issues. However, recruiting behavior of the type studied here has wider implications, for example, for DSGE business cycle models. It

is of interest to study them, in particular in light of the finding of counter-cyclical job values and hiring from non-employment. In this vein, consider a recent discussion of the role of wage cyclicality in these models. Basu and House (2016) and Bils, Klenow, and Malin (2016) make the point that wages and Kudlyak's (2014) user cost of labor do not display much rigidity and are pro-cyclical. The former paper notes that monetary business-cycle models lean heavily on price and wage rigidity. But while there is substantial evidence that prices do not adjust frequently, there is much less evidence of wage rigidity. Hence, the cyclical behavior of wages is important for business cycle analysis, in particular for New Keynesian models. What are the analog repercussions of the current paper, which focuses on the cyclical behavior of job values, rather than wages? ¹⁸How would the counter-cyclical patterns found here be reflected in business cycle models? This is the subject of a separate analysis I have undertaken (see Faccini and Yashiv (2016)). The analysis embeds the current one in a New Keynesian DSGE model, examining the effects of technology and monetary policy shocks. It turns out that hiring costs of the type examined here offset the effects of price frictions in the presence of shocks. This interaction between hiring and price frictions is shown to generate substantial and wide-ranging effects, which are delineated and explained in the cited paper.

¹⁸The relations of job values with wages, via the labor share, were explored in Section 8, and with the user cost in Section 7, showing that they follow very different cyclical behavior. Volatility and cyclicality of all recruiting variables were well explained using these job values.

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Tables and Figures

Table 1
Alternative Formulations of The Recruiting Equation (1)

Linear Costs Models

	paper	firm size	LHS, costs, arguments
1	Pissarides (2000, chapter 1)	single job	v, p
2	Pissarides (2000, chapter 2)	single job	v
3	Shimer (2005)	single job	v
4	Hall (2005)	single job	v
5	Mortensen and Nagypal (2007)	single job	v
6	Hall and Milgrom (2008)	large	v
7	Hagedron and Manovskii (2008)	single job	$v : c^K p + c^w p^\xi$
8	Hall (2016)	single job	v
9	Christiano et al (2016)	large	$\frac{h}{n}$

RHS, job value				
	f (production)	w (wages)	s (separation)	ρ (discounting)
1	exo, stoch	Nash	exo, constant	constant
2	exo, stoch	Nash	endo, stoch	constant
3	exo, stoch	Nash	exo, stoch	constant
4	exo, stoch	sticky	exo, constant	constant
5	exo, stoch	Nash / rigid/Calvo	exo, constant	constant
6	exo, stoch	alternating offers	exo, constant	constant
7	exo, stoch	Nash	exo, constant	constant
8	exo, stoch	Nash/alternating offers	exo, constant	from stock market
9	$h_t = l_t$	alternating offers	exo, constant	GE, IMRS

Convex Costs Models

	paper	size	LHS, costs, arguments	
			arguments	function
1	Merz and Yashiv (2007)	large	$\frac{h}{n}, \frac{i}{k}, f$	linear-convex
2	Gertler and Trigari (2009)	large	$\frac{h}{n}$	quadratic
3	Gali (2011)	large	$\frac{h}{u}$	power
4	Acemoglu and Hawkins (2014)	large	v	convex

RHS, job value				
	f (production)	w (wages)	s (separation)	ρ (discounting)
1	$e^{z_t} n_t^\alpha k_t^{1-\alpha}$	exo, stoch	exog, stoch	WACC
2	$z_t n_t^\alpha k_t^{1-\alpha}$	Nash, Calvo	exo, constant	GE, IMRS
3	$A_t N_t^{1-\alpha}$	Nash, Calvo	exo, constant	GE, IMRS
4	$y(n; z)$	Intrafirm bargaining	exo, constant	constant

Notes:

1. The table presents components of the recruiting equations in key papers, spelled out in full in Appendix A. These equations all have recruiting costs on their left hand side (LHS) and some measure of job value on their right hand side (RHS).

2. Abbreviations used:

exo=exogenous

endo=endogenous

stoch= stochastic

v =vacancies, h =hires, n =employment, p =productivity

GE=General Equilibrium

IMRS=Intertemporal Rate of Substitution

WACC=Weighted Average Cost of Capital

Table 2
Co-Movement of Hiring Rates from Non Employment ($\frac{h_t^1}{n_t}$) and GDP (f_t)
 logged, HP-filtered

Cross-Correlations

$\rho(\frac{h_t^1}{n_t}, f_{t+i})$

i	-8	-4	-1	0	1	4	8
	-0.15	-0.35	-0.39	-0.30	-0.15	0.11	0.23

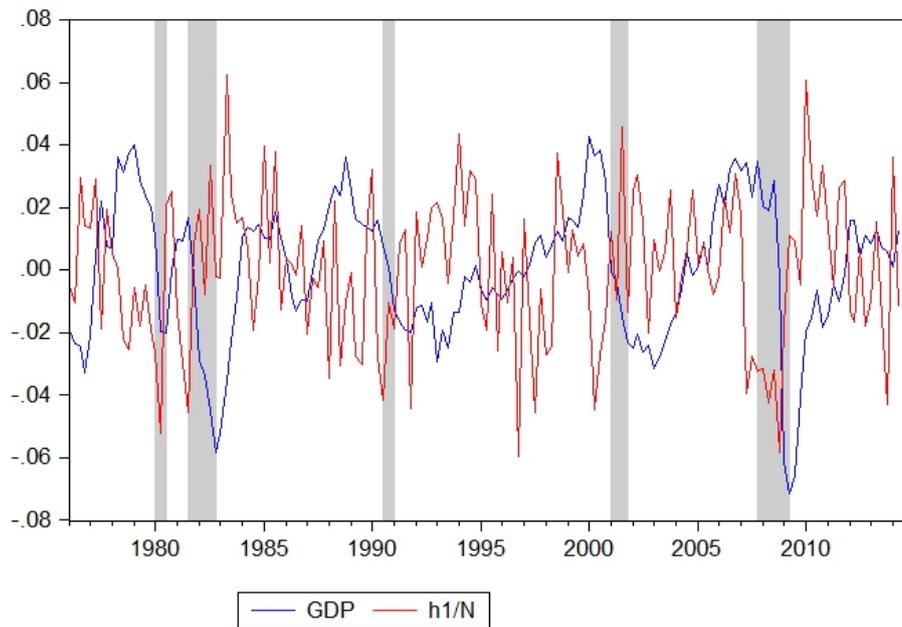


Figure 1: Cyclicity of the hiring rate from non-employment $\frac{h_t^1}{n_t}$

Notes:

1. NBER-dated recessions are shaded.
2. The blue line is GDP, f_t in terms of the model; the red line is the rate of hiring from non-employment, $\frac{h_t^1}{n_t}$ in the model

Table 3
Co-Movement of Hiring Rates from Employment (job to job flows, $\frac{h_t^2}{n_t}$) and GDP (f_t)
 logged, HP-filtered

Cross-Correlations

$\rho(\frac{h_t^2}{n_t}, f_{t+i})$

i	-8	-4	-1	0	1	4	8
	-0.13	0.26	0.64	0.68	0.66	0.28	-0.05

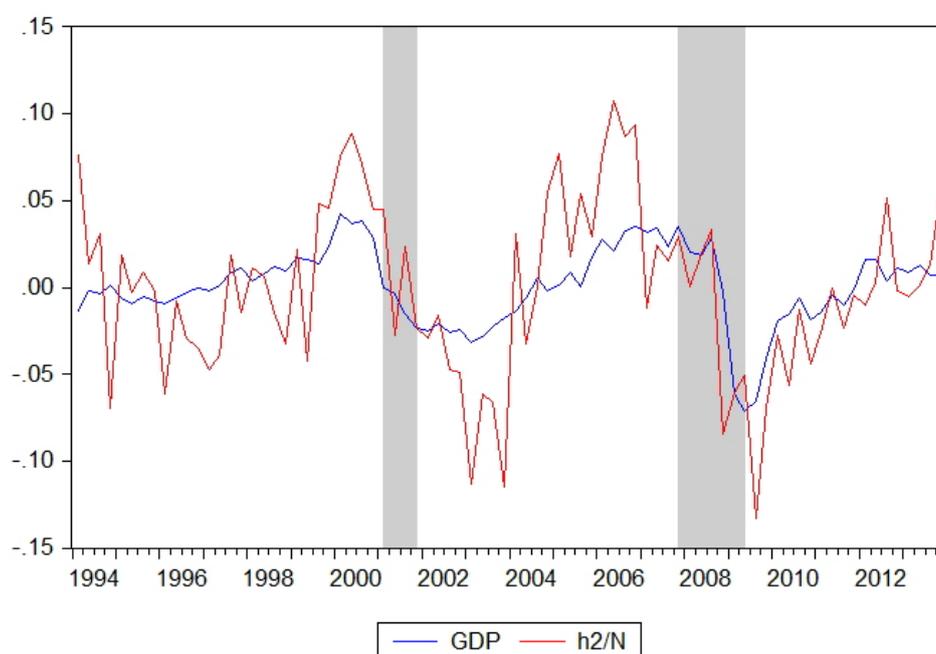


Figure 2: Cyclical relationship of the hiring rate from other employment $\frac{h_t^2}{n_t}$

Notes:

1. NBER-dated recessions are shaded.
2. The blue line is GDP, f_t in terms of the model; the red line is the rate of hiring from other employment, $\frac{h_t^2}{n_t}$ in the model. Data are available only from 1994.

Table 4
Co-Movement of Vacancy Rates ($\frac{v_t}{n_t}$) and GDP (f_t)

logged, HP-filtered

Cross-Correlations

	$\rho(\frac{v_t}{n_t}, f_{t+i})$						
i	-8	-4	-1	0	1	4	8
	-0.26	0.29	0.82	0.89	0.83	0.39	-0.13

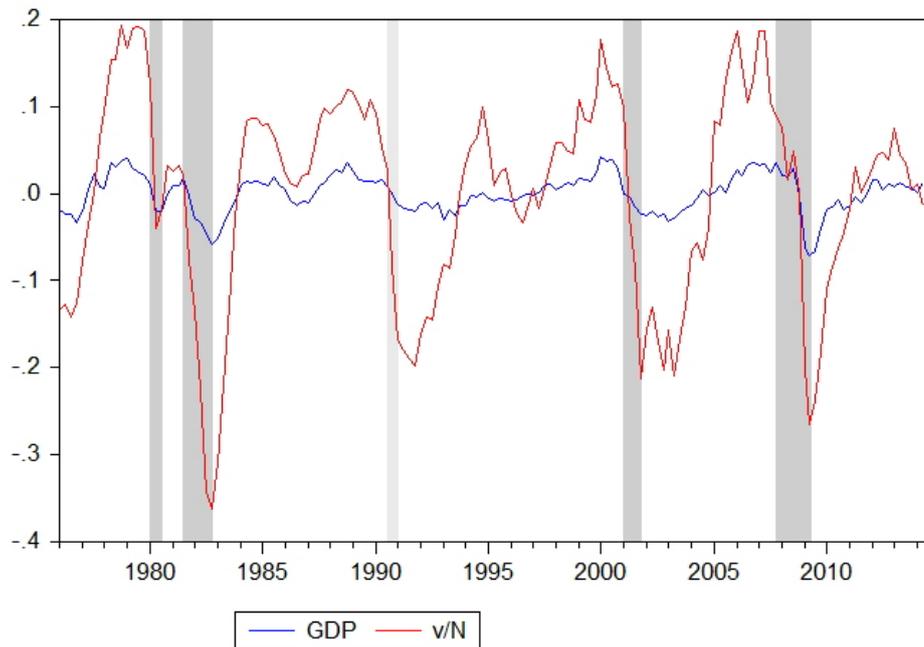


Figure 3: Cyclical relationship of vacancy rates $\frac{v_t}{n_t}$

Notes:

1. NBER-dated recessions are shaded.
2. The blue line is GDP, f_t in terms of the model; the red line is the vacancy rate, $\frac{v_t}{n_t}$ in the model.

Table 5
Total Hiring Flows (NSA, 000s)

Moments
Sample: 2001 : 1 – 2014 : 06

	CPS	JOLTS
Mean	8,595	4,698
Median	8,609	4,765
Std. Dev.	496	484
C.O.V	0.06	0.10
Skewness	0.25	-0.25
Kurtosis	2.42	2.14

Table 6
Stochastic Behavior of the Gross Hiring Rate
and Other Labor Market Variables

Co-Movement (contemporaneous correlation) with GDP

logged, HP filtered

$\frac{h_t^1}{n_t}$	$\frac{h_t^1}{u_t+o_t}$	$\frac{u_t+o_t}{pop_t}$	$\frac{1}{\frac{n_t}{pop_t}}$
-0.25	0.53	-0.72	-0.82

Notes:

1. $\frac{h_t^1}{n_t}$ is the rate of hiring from non-employment.
2. $\frac{h_t^1}{u_t+o_t}$ is the job-finding rate.
3. $\frac{u_t+o_t}{pop_t}$ is the non-employment rate.
4. $\frac{1}{\frac{n_t}{pop_t}}$ is the inverse employment rate (out of working age population).

Table 7

Descriptive Sample Statistics
 Quarterly, U.S. data

a. 1976:1-2013:4 ($n = 152$)									
Variable	$\frac{f}{k}$	τ	$\frac{i}{k}$	δ	$\frac{wn}{f}$	$\frac{h^1}{n}$	$\frac{v}{n}$	ψ^1	β
Mean	0.14	0.38	0.024	0.02	0.62	0.126	0.031	0.125	0.99
Standard Deviation	0.01	0.05	0.003	0.003	0.02	0.010	0.007	0.010	0.005

b. 1994:1-2013:4 ($n = 80$)								
Variable	$\frac{f}{k}$	τ	$\frac{i}{k}$	δ	$\frac{wn}{f}$	$\frac{h}{n} = \frac{h^1+h^2}{n}$	$\frac{v}{n}$	$\psi = \psi^1 + \psi^2$
Mean	0.15	0.34	0.026	0.02	0.61	0.178	0.028	0.178
Standard Deviation	0.01	0.005	0.002	0.002	0.03	0.012	0.005	0.012

β	
Mean	0.99
Standard Deviation	0.005

Notes:

All variables are defined in Section 4.1 and in Appendix C.

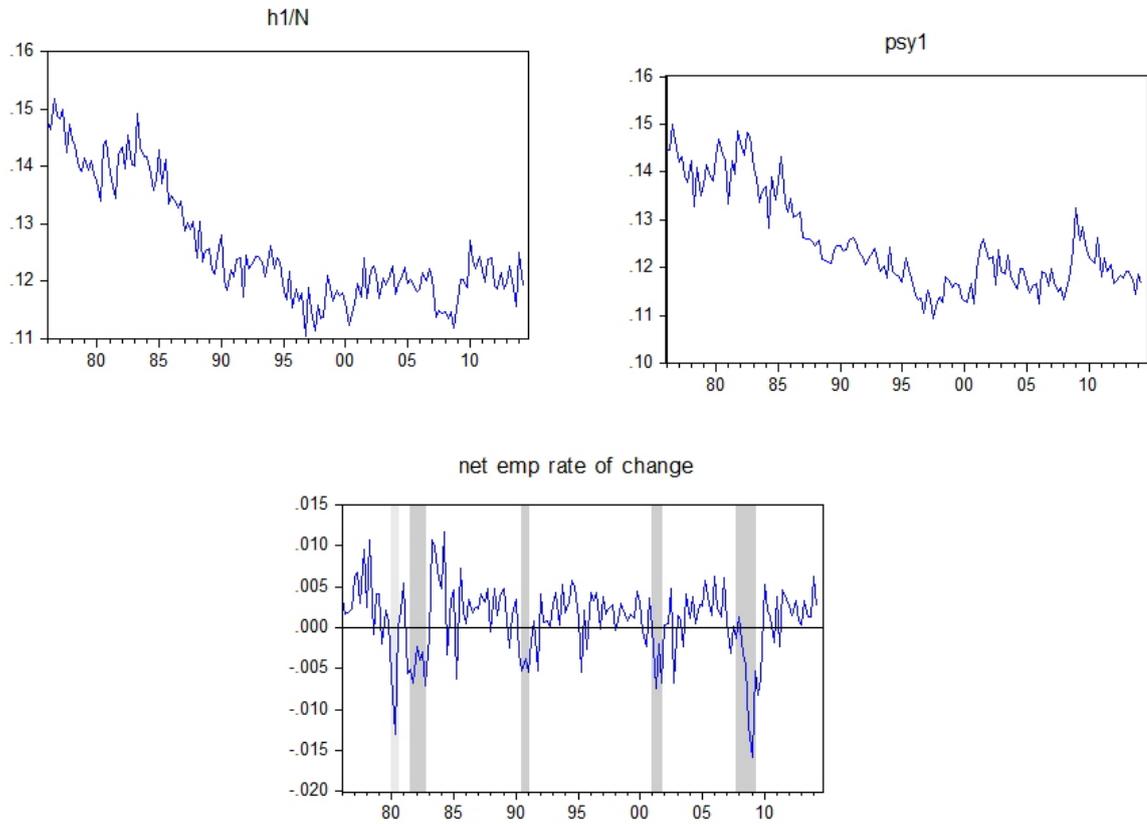


Figure 4: Gross and Net Worker Flows Rates

Notes:

1. The graph labeled h1/N shows the hiring rate from non-employment $\frac{h_t^1}{n_t}$.
2. The graph labeled psy1 shows the separation rate from employment to non-employment ψ_t^1 .
3. The graph labeled net emp rate of change shows the rate of change of the stock of employment $\frac{n_t - n_{t-1}'}{n_{t-1}}$. NBER-dated recessions are shaded.

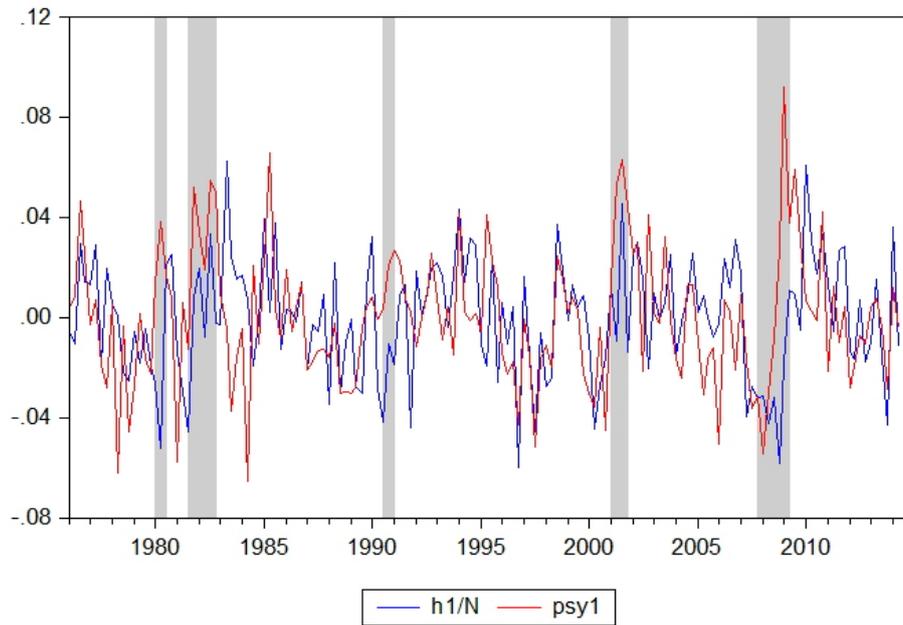


Figure 5: Hiring and separation rates, to and from non-employment

Notes:

1. The series labeled h1/N shows the hiring rate from non-employment $\frac{h_t^1}{n_t}$.
2. The series labeled psy1 shows the separation rate from employment to non-employment ψ_t^1 .
3. Both series are logged and HP-filtered. NBER-dated recessions are shaded.

Table 8
GMM Estimates

	specification	e_1	e_2	e_{31}	e_{32}	α	J-Statistic
<i>a</i>	benchmark	77.3 (6.3)	9.1 (1.0)	-2.8 (1.2)	-19.6 (0.9)	0.66 (0.003)	51.6 (0.74)
<i>b</i>	constrained case $\lambda_1 = 0.9; \lambda_2 = 0$ 1976 – 2013	32.2 (6.4)	2.3 (0.4)	-1.5 (0.9)	–	0.65 –	83.9 (0.30)
<i>c</i>	Tobin's q for N	0 –	30.8 (0.9)	0 –	0 –	0.70 (0.003)	61.9 (0.48)
<i>d</i>	Standard matching model $\eta_2 = 1, \lambda_1 = \lambda_2 = 0$	0 –	9.3 (0.1)	0 –	0 –	0.77 (0.002)	62.5 (0.46)

Notes:

1. The tables report point estimates with standard errors in parentheses. The J-statistic is reported with p value in parentheses.

2. The following parameter values are set unless indicated otherwise: $\lambda_1 = 0.6; \lambda_2 = 0.2; \eta_1 = \eta_2 = 2, \eta_{31} = \eta_{32} = 1$.

3. The sample period is 1994:1 – 2013:4, except for Row b where it is 1976:1-2013:4.

Table 9
Estimated Marginal Costs – Data Moments
1994 : 1 – 2013 : 4

	benchmark	constrained	Tobin's Q for N	Std matching model
mean	0.12	0.13	0.90	0.97
median	0.12	0.13	0.89	1.00
std.	0.03	0.01	0.03	0.13
auto-correlation	0.91	0.80	0.55	0.92

Notes:

1. The series in the table are the LHS of the estimated equation (reported in Table 8) namely $(1 - \tau_t) \frac{g_{v_t}}{q_t \frac{I_t}{N_t}}$.

2. The sample period is 1994:1 – 2013:4, except for column “constrained” where it is 1976:1-2013:4.

Table 10
Variance Decomposition ($T = 30$)

	1	2	3	4
	benchmark	constrained	Tobin's q	Std model
$var(PV_{t,T})$	0.01	0.01	0.01	0.01
$\frac{\Omega^r \Omega^f E(MP)}{1-\Omega} \sum_{j=1}^T (\Omega)^{j-1} cov(P_t, g_{t+j}^r)$ ----- $var(PV_{t,T})$	0.04	0.01	0.09	0.07
$\frac{\Omega^r \Omega^f E(MP)}{1-\Omega} \sum_{j=1}^T (\Omega)^{j-1} cov(P_t, g_{t+j}^f)$ ----- $var(PV_{t,T})$	-0.02	-0.001	0.04	0.03
$\frac{\Omega^r \Omega^f E(MP)}{1-\Omega} \sum_{j=2}^T (\Omega)^{j-1} cov(P_t, g_{t+j}^s)$ ----- $var(PV_{t,T})$	-0.007	0.07	0.06	0.06
$\frac{\Omega^r \Omega^f \sum_{j=1}^T (\Omega)^{j-1} cov(P_t, MP_{t+j})}{var(PV_{t,T})}$	0.74	0.60	0.78	0.62
residual	0.24	0.32	0.02	0.21

Notes:

1. See Section 6.2 for a discussion and Appendix E for full details of the decomposition.
2. The four specifications follow the estimates of Table 8.
3. The basic decomposition equation is:

$$\begin{aligned}
 var(PV_t) \cong & \frac{\Omega^r \Omega^f E(MP)}{1-\Omega} \sum_{j=1}^T (\Omega)^{j-1} cov(PV_t, g_{t+j}^r) + \\
 & \frac{\Omega^r \Omega^f E(MP)}{1-\Omega} \sum_{j=1}^T (\Omega)^{j-1} cov(PV_t, g_{t+j}^f) + \\
 & \frac{\Omega^r \Omega^f E(MP)}{1-\Omega} \sum_{j=2}^T (\Omega)^{j-1} cov(PV_t, g_{t+j}^s) + \\
 & \Omega^r \Omega^f \sum_{j=1}^T (\Omega)^{j-1} cov(PV_t, MP_{t+j})
 \end{aligned}$$

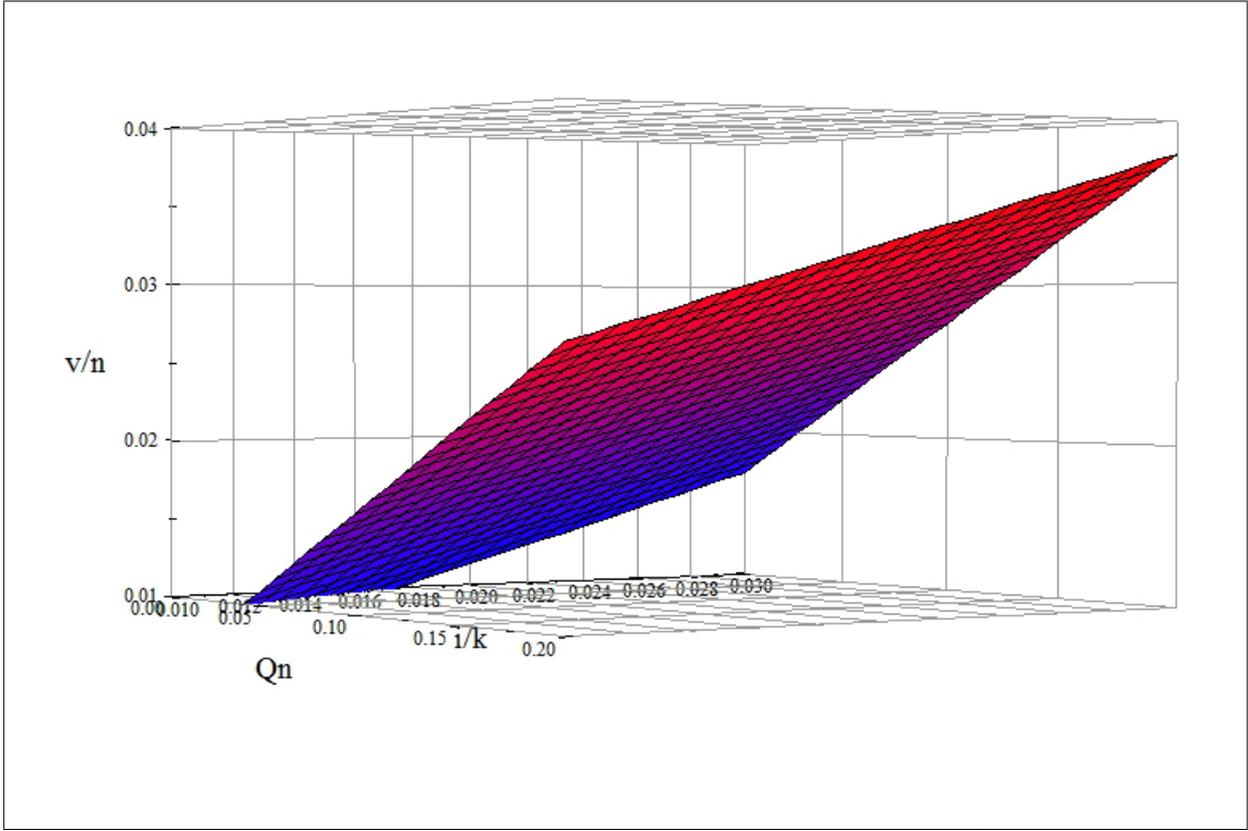


Figure 6: Estimated Relationships of Recruitment ($\frac{v_t}{n_t}$), Job Values ($\frac{Q_t^N}{n_t}$), and Investment Rates ($\frac{i_t}{k_t}$)

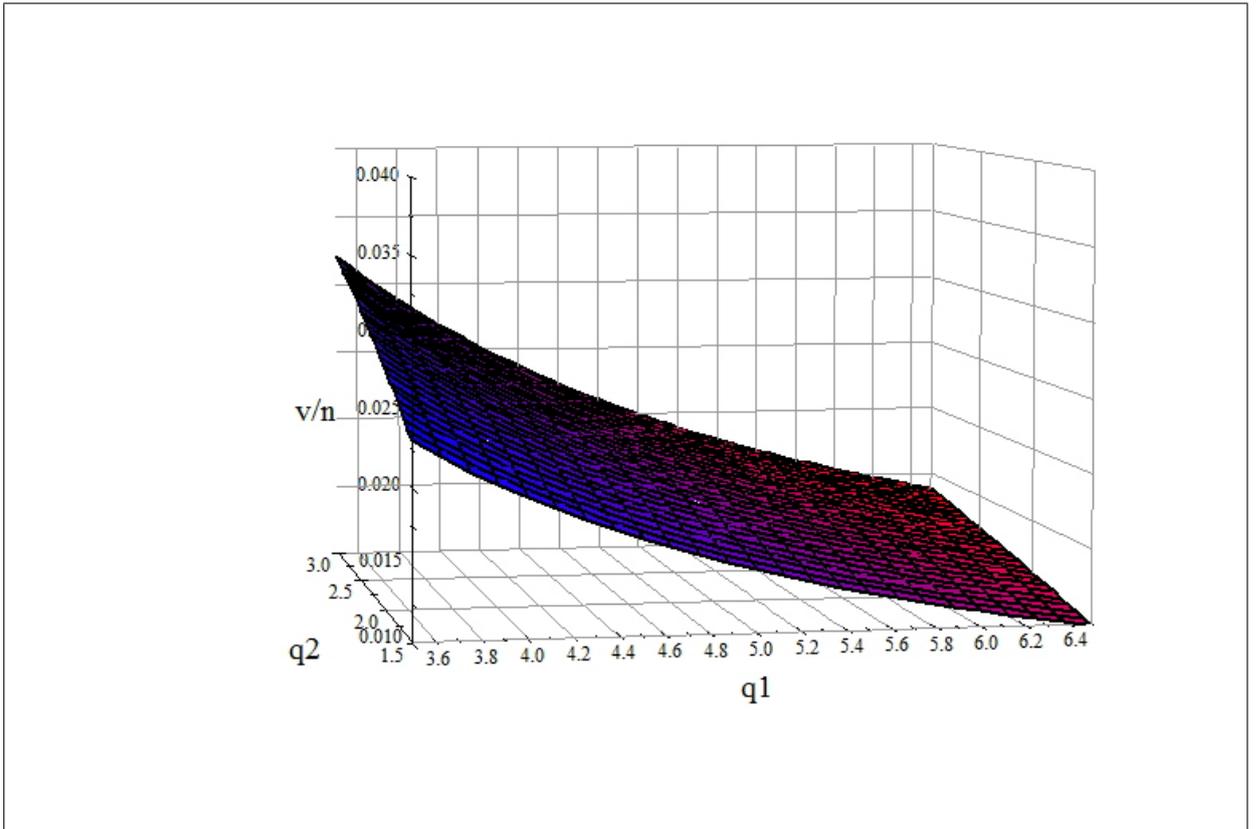


Figure 7: Estimated Relationships of Recruitment ($\frac{v_t}{n_t}$) and Job Filling Rates (q_t^1, q_t^2)

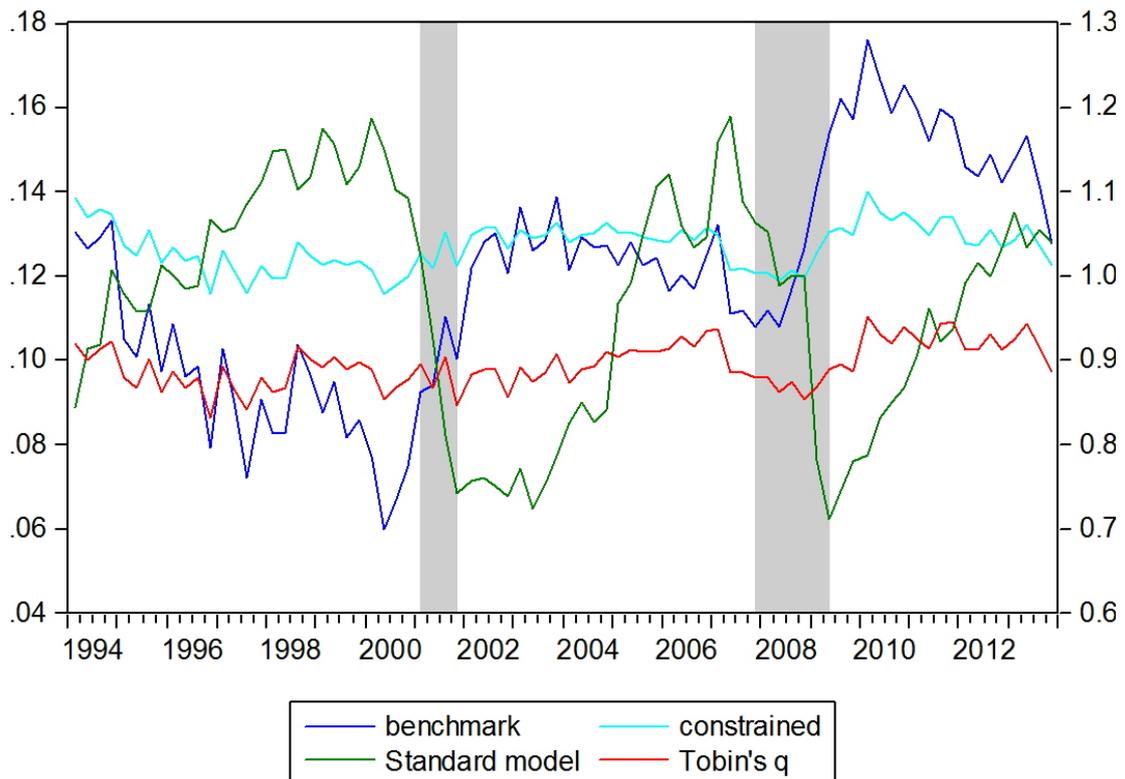


Figure 8: Job Values Estimates Across Models

Notes:

1. Benchmark refers to the preferred specification of Table 8, row (a). Constrained refers to the specification of Table 8, row (b). Their values are given on the left axis. See the corresponding columns in Table 9.
2. Tobin's q and standard model refer to the specifications of Table 8, rows (c) and (d), respectively. Their values are given on the right axis. See the corresponding columns in Table 9.
3. NBER-dated recessions are shaded.

Table 11
Job Value Cyclicalty

Cross-Correlations of LHS of the Vacancy Optimality Equation with GDP

$$(1 - \tau_t) \frac{g_{v_t}}{q_t} = E_t \left[\rho_{t+1} (1 - \tau_{t+1}) \left[\begin{array}{c} f_{n_{t+1}} - g_{n_{t+1}} - w_{t+1} \\ + (1 - \psi_{t+1}) \frac{g_{v_{t+1}}}{q_{t+1}} \end{array} \right] \right]$$

$\rho(\text{LHS}_t, \mathbf{f}_{t+i})$
HP filtered ($\lambda = 1600$)

Benchmark Model

<i>i</i>	-8	-4	-1	0	1	4	8
<i>y</i>	-0.04	-0.46	-0.67	-0.63	-0.49	0.04	0.33

Constrained Case

<i>i</i>	-8	-4	-1	0	1	4	8
<i>y</i>	0.04	-0.29	-0.38	-0.29	-0.14	0.21	0.32

Tobin's q

<i>i</i>	-8	-4	-1	0	1	4	8
<i>y</i>	-0.28	-0.24	0.03	0.13	0.27	0.41	0.19

Standard Model

<i>i</i>	-8	-4	-1	0	1	4	8
<i>y</i>	-0.26	0.38	0.85	0.90	0.79	0.39	-0.18

Notes:

This equation is equation (15) in the text.

Table 12
The Labor Share, Approximated Job Values and GDP
Cross-Correlations
 logged, HP filtered ($\lambda = 1600$)

a. $\rho\left(f_t, \frac{w_{t+i}}{f_{t+i}}\right)$

i	-8	-4	-1	0	1	4	8
	-0.36	-0.38	-0.29	-0.23	-0.02	0.53	0.46

b. $\rho\left(f_t, PV_{t+i}(MP)\right)$

$$PV_t(MP_{t+s}) = \sum_{s=1}^T \left(\frac{1}{(1-\psi_t)} \prod_{i=1}^s \rho_{t+i} \frac{\frac{f_{t+i}}{n_{t+i}}}{\frac{f_{t+i-1}}{n_{t+i-1}}} (1-\psi_{t+i-1}) \right) (1-\tau_{t+s}) \left[\alpha - \frac{w_{t+s}}{f_{t+s}} \right].$$

i	-8	-4	-1	0	1	4	8
	0.45	-0.07	-0.47	-0.54	-0.54	-0.39	-0.15

Notes:

- a. Panel a shows dynamic correlations between the labor share $\frac{w_{t+i}}{f_{t+i}}$ and GDP f_t .
- b. Panel b shows dynamic correlations between the approximated job value given by $PV_t(MP_{t+s})$ and GDP f_t .
- c. There are two aspects to the approximation in PV_t : it ignores the $\frac{g_{t+1}}{f_{t+1}}$ term in the optimality equation (15) and it truncates the infinite sum at T .

Table 13a
Volatility of Recruiting Variables

	std
$\frac{i_t}{k_t}$	0.07
q_t^1	0.12
q_t^2	0.08
$\frac{v_t}{n_t}$	0.11
$\frac{h_t}{n_t}$	0.02
$\frac{h_t^1}{n_t}$	0.02

Table 13b
Moments of the Determinants of Recruitment

	f_t	$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$
std	0.02	0.12
ρ		-0.63

Table 13c
Co-Movement of Recruiting Variables

$\rho(\text{row,column})$	f_t	$\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}$
$\frac{i_t}{k_t}$	0.87	-0.83
q_t^1	-0.89	0.67
q_t^2	-0.79	0.39
$\frac{v_t}{n_t}$	0.91	-0.56
$\frac{h_t}{n_t}$	0.27	0.15
$\frac{h_t^1}{n_t}$	-0.28	0.78

Notes:

1. All series are logged and HP-filtered.
2. Q_t^N is computed using the point estimates of row (a) in Table 8.

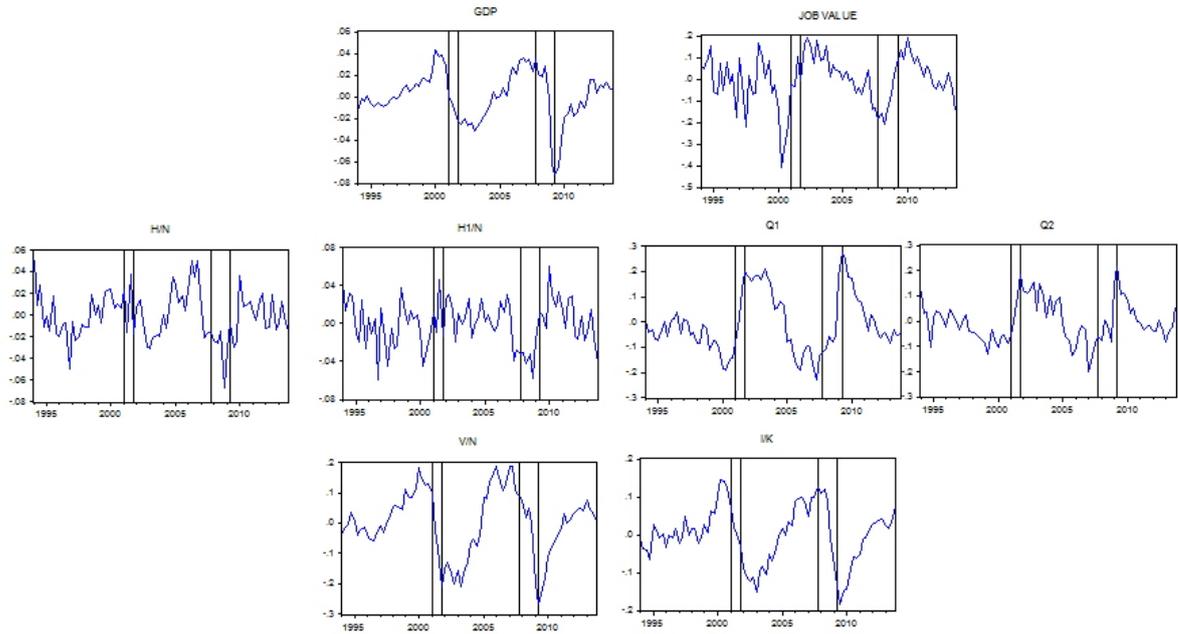


Figure 9: Key Data Series for the Cyclical Analysis

Notes:

1. The series shown are GDP (f_t), job value (Q_t^N , computed using the point estimates of row (a) in Table 8), total hiring rate H/N ($\frac{h_t}{n_t}$), hiring rate from non-employment H1/N ($\frac{h_t^1}{n_t}$), job filling rate from non-employment (q_t^1), job filling rate from other employment (q_t^2), the vacancy rate V/N ($\frac{v_t}{n_t}$), and the investment rate I/K ($\frac{i_t}{k_t}$).

2. All series are logged and HP-filtered.

3. NBER-dated recessions are shown between the vertical lines.

Table 14: Variance Decomposition: The Vacancy Rate

	variance	relative to $var(\frac{v_t}{n_t})$
$var(\frac{v_t}{n_t})$	$2.3 * 10^{-5}$	1
$var\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$2.7 * 10^{-6}$	0.12
$var\left(\frac{(e_{31}q_t^1+e_{32}q_t^2)\frac{i_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$2.5 * 10^{-5}$	1.08
$cov\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{(e_{31}q_t^1+e_{32}q_t^2)\frac{i_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$2.4 * 10^{-6}$	0.11

Table 15

Co-Movement: The Vacancy Rate

$\rho\left(\frac{v_t}{n_t}, f_t\right)$	0.91
$\rho\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, f_t\right)$	0.26
$\rho\left(\frac{-(e_{31}q_t^1+e_{32}q_t^2)\frac{i_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, f_t\right)$	0.92
$\rho\left(\frac{v_t}{n_t}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	-0.56
$\rho\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	0.49
$\rho\left(\frac{-(e_{31}q_t^1+e_{32}q_t^2)\frac{i_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	-0.77

Notes:

1. The vacancy rate variance decomposition is discussed and explained in Section 9. The bottom two tables show the correlations of the vacancy rate and its components with GDP and the intra-correlations.

2. All series are logged and HP-filtered. Q_t^N is computed using the point estimates of row (a) in Table 8.

Table 16
Variance Decomposition: The Total Hiring Rate

	variance	relative to $var\left(\frac{h_t}{n_t}\right)$
$var\left(\frac{h_t}{n_t}\right)$	$1.5 * 10^{-4}$	1
$var\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)^2}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$1.8 * 10^{-4}$	1.19
$var\left(\frac{(q_t^1+q_t^2)(e_{31}q_t^1+e_{32}q_t^2)\frac{h_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$4.4 * 10^{-4}$	2.90
$cov\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)^2}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{(q_t^1+q_t^2)(e_{31}q_t^1+e_{32}q_t^2)\frac{h_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$2.3 * 10^{-4}$	1.55

Table 17
Co-Movement: The Total Hiring Rate

$\rho\left(\frac{h_t}{n_t}, f_t\right)$	0.27
$\rho\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)^2}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, f_t\right)$	-0.65
$\rho\left(\frac{-(q_t^1+q_t^2)(e_{31}q_t^1+e_{32}q_t^2)\frac{h_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, f_t\right)$	0.82
$\rho\left(\frac{h_t}{n_t}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	0.15
$\rho\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)^2}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	0.99
$\rho\left(\frac{-(q_t^1+q_t^2)(e_{31}q_t^1+e_{32}q_t^2)\frac{h_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	-0.86

Notes:

Same as for Tables 14 and 15; except that the bottom two tables pertain to the total hiring rate and its components.

Table 18
Variance Decomposition: The Hiring Rate (from non-employment)

	variance	relative to $var(\frac{h_t^1}{n_t})$
$var(\frac{h_t^1}{n_t})$	$1.2 * 10^{-5}$	1
$var\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)q_t^1}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$1.4 * 10^{-4}$	11.4
$var\left(\frac{q_t^1(e_{31}q_t^1+e_{32}q_t^2)\frac{f_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$9.3 * 10^{-5}$	7.6
$cov\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)q_t^1}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{q_t^1(e_{31}q_t^1+e_{32}q_t^2)\frac{f_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}\right)$	$1.1 * 10^{-4}$	9.0

Table 19
Co-Movement: The Hiring Rate (from non-employment)

$\rho\left(\frac{h_t^1}{n_t}, f_t\right)$	-0.28
$\rho\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)q_t^1}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, f_t\right)$	-0.68
$\rho\left(\frac{-q_t^1(e_{31}q_t^1+e_{32}q_t^2)\frac{f_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, f_t\right)$	0.84

$\rho\left(\frac{h_t^1}{n_t}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	0.78
$\rho\left(\frac{\frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}(q_t^1+q_t^2)q_t^1}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	0.997
$\rho\left(\frac{-q_t^1(e_{31}q_t^1+e_{32}q_t^2)\frac{f_t}{k_t}}{e_2[(1-\lambda_1-\lambda_2)+\lambda_1q_t^1+\lambda_2q_t^2]^2}, \frac{Q_t^N}{(1-\tau_t)\frac{f_t}{n_t}}\right)$	-0.84

Notes:

Same as for Tables 14 and 15; except that the bottom two tables pertain to the hiring rate from non-employment and its components.

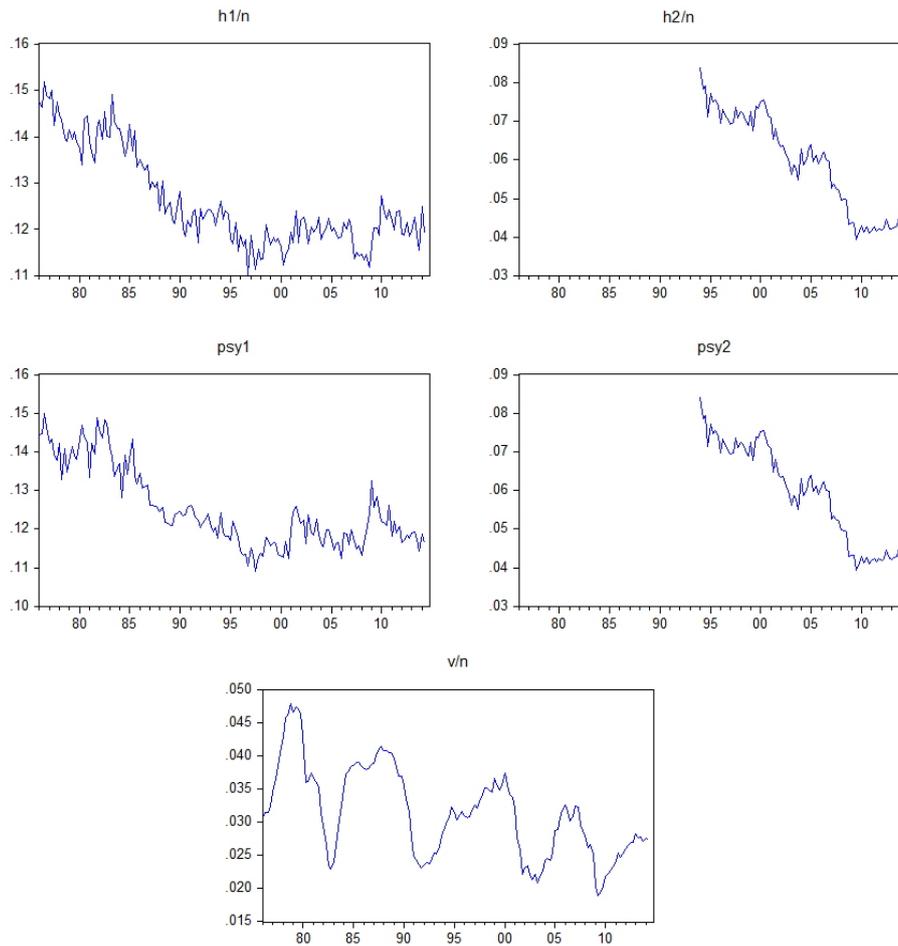


Figure 10: The Secular Decline in Worker Flows and Vacancy Rates

Notes:

1. The series shown are the hiring rate from non-employment $H1/N$ ($\frac{h_t^1}{n_t}$), hiring rate from other employment $H2/N$ ($\frac{h_t^2}{n_t}$), the separation rate from employment to non-employment ψ_1 (ψ_t^1), the flow rate from employment to other employment ψ_2 (ψ_t^2), and the vacancy rate V/N ($\frac{v_t}{n_t}$).

2. All series are raw data, not filtered.

Table 20
Decline in Labor Market Fluidity (Section 10)

$$\frac{Q_t^N}{\frac{f_t}{n_t}} = (1 - \tau) \frac{g_v}{q_t^1 \frac{f}{n}} = (1 - \tau_t) e_3 \frac{i_t}{k_t} + \frac{(1 - \tau_t)}{q_t^1} e_2 \left(1 - \lambda_1 + \lambda_1 q_t^1\right)^2 \frac{v_t}{n_t}$$

Data Averages

	1976:1-1995:4	1996:1-2013:4
$\frac{v_t}{n_t}$	0.035	0.028
τ_t	0.41	0.34
q_t^1	4.0	4.4
$\frac{i_t}{k_t}$	0.022	0.026

Parameter Point Estimates

e_2	2.3
e_3	-1.5
λ_1	0.9

Job Value Estimates

	1976:1-1995:4	1996:1-2013:4
$\frac{Q_t^N}{\frac{f_t}{n_t}}$	0.135	0.126

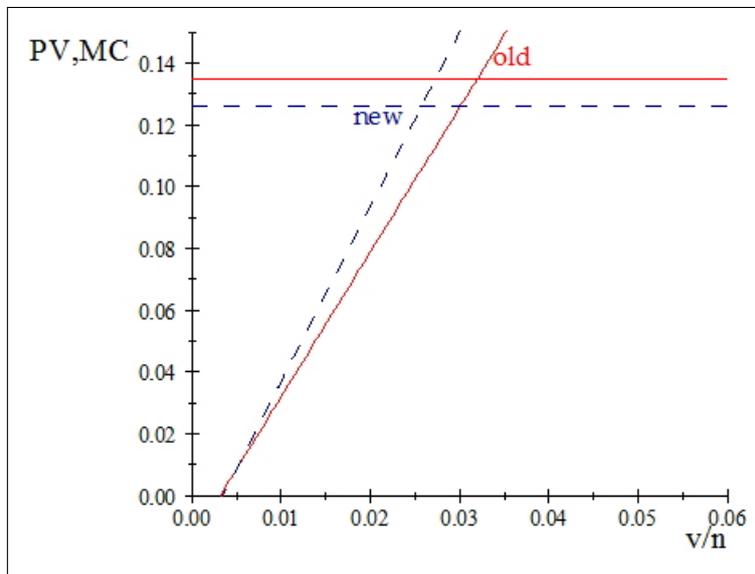


Figure 11: Job Values and Marginal Costs Across Sub-Periods