Prepared for ESSIM 2008

U.S. LABOR MARKET DYNAMICS AND THE BUSINESS CYCLE

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May 17, 2008

Abstract

The characterizations of U.S. labor market dynamics and their implications for the study of business cycles are topics of debate. Different empirical studies have yielded contradictory findings, conflicting views have emerged regarding business cycle implications, and there is disagreement as to how much the search and matching model — a key model in this context — can explain the data.

This paper tries to determine what facts can be established, what are their implications for the business cycle, and what remains to be further investigated. It then re-examines the model to see whether it fits the data, what generates the fit, and where it fails.

The findings are mixed. Certain data facts are clarified and the partial equilibrium version of the search and matching model is shown to fit most of these facts. Concurrently, there are open issues with respect to data characterization and model-data fit.

Key words: labor market dynamics, search, matching, business cycles, gross worker flows, job finding, separation, hiring, partial equilibrium, general equilibrium.

JEL codes: E24, J63, J64.

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1 Introduction

The characterizations of U.S. labor market dynamics and their implications for the study of business cycles are topics of debate. There are three, interrelated issues of concern:

First, different empirical studies of U.S. gross worker flows and labor market dynamics over the past two decades have yielded contradictory findings. Reading these different studies, it is not easy to get a sense of what the key data moments are and how they compare with each other.

Second, debates have emerged regarding the implications of these worker flows for the understanding of the business cycle. The 'conventional wisdom,' based on the reading of Blanchard and Diamond (1989, 1990), Davis and Haltiwanger (1999), and Bleakley, Ferris, and Fuhrer (1999), was that worker separations from jobs are the more dominant cyclical phenomenon than hirings of workers, and that therefore it is important to analyze the causes for separations or job destruction. In particular, it was believed that in order to study the business cycle it is crucial to understand the spikes and volatility of employment destruction. This view was challenged by Hall (2005) and Shimer (2007), who claimed that separations are roughly constant over the cycle, and that the key to the understanding of the business cycle is in the cyclical behavior of the job finding rate.

Third, there is also disagreement as to how much the search and matching model – a key model in this context – can explain the data. While the early studies of Merz (1995), Andolfatto (1996), and den Haan et al (2000) provided empirical support for the model, a number of subsequent papers claimed that the model does not fit the data (most notably, Shimer (2005)).

This paper aims at clarifying the picture. It tries to determine what facts can be established,

[1] *I am grateful to Fabiano Bastos, Wouter den Haan, Robert Hall, Dale Mortensen, Chris Pissarides and Robert Shimer for useful conversations, to seminar participants at the SED meetings in Prague (June 2007), UCL, Tel Aviv University, Oxford University, the Bank of England, and the University of Bristol for useful comments, to Olivier Blanchard, Joe Ritter, Jeff Fuhrer, Hoyt Bleakley, Ann Ferris, Elisabeth Walat, Bruce Fallick, and Robert Shimer for the provision of their data, and to Darina Waisman and Gili Greenberg for able research assistance. Any errors are mine.*

what are their implications for the business cycle, and what remains to be further investigated. The paper examines CPS data used by five key studies, as well as JOLTS data, and establishes the key facts. It then re-examines the model – in partial equilibrium form and in general equilibrium form – to see whether it fits the data, what generates the fit, and where it fails.

The paper proceeds as follows: Section 2 discusses the background literature and the current debates. Section 3 examines data issues, establishing a list of facts and a list of issues in need of further research. Section 4 examines a partial equilibrium version of the search and matching model. Section 5 examines a general equilibrium version of this model. In each of these last two sections the model is presented, the empirical methodology used is outlined, calibration values are delineated, and simulation results are reported and discussed. Section 6 concludes.

2 The Literature

In this section I discuss the findings of recent literature and the ensuing debates. I do so first in terms of the data and then in terms of the search and matching model.

Data.

In terms of volatility, Blanchard and Diamond (1989, 1990) found that the amplitude of fluctuations in the flow out of employment is larger than that of the flow into employment, implying that changes in employment are dominated by movements in job destruction rather than in job creation. Similarly, Bleakley, Ferris, and Fuhrer (1999) found that once the trend is removed, the flows out of employment have more than twice the variance of the flows into employment. These studies placed the emphasis on comparing hiring rates to the separation rate from employment. But recently, Hall (2005) and Shimer (2007) claimed that separation rates are not as volatile as job finding rates (not hiring rates) and that they can be taken roughly as constant (in detrended terms). These later studies typically refer to the total separation rate, which includes job to job flows.

In terms of cyclical co-movement, Blanchard and Diamond (1989, 1990) found sharp differences between the cyclical behavior of the various flows. In particular, the EU flow increases in a recession while the EN flow decreases; the UE flow increases in a recession, while the NE flow decreases. Ritter (1993) reported that the net drop in employment during recessions is clearly dominated by job separations. Bleakley, Ferris, and Fuhrer (1999) found that the flow into voluntary quits declines fairly sharply during recessions, consistent with the notion that quits are largely motivated by prospects for finding another job. "Involuntary" separations – both layoffs and terminations – rise sharply during recessions and gradually taper off during the expansions that follow.

More recently, a new picture of worker flows cyclicality has been proposed. Hall (2005) developed estimates of separation rates and job-finding rates for the past 50 years, using historical data informed by the detailed recent data from JOLTS. He found that the separation rate is nearly constant while the job-finding rate shows high volatility at business-cycle and lower frequencies. He concluded that this necessitates a revised view of the labor market: during a recession unemployment rises entirely because jobs become harder to find. Recessions involve no increases in the flow of workers out of jobs. Another important finding from the new data is that a large fraction of workers departing jobs move to new jobs without intervening unemployment. Shimer (2007) reported that the job finding probability is strongly procyclical while the separation probability is nearly acyclical, particularly during the last two decades. He showed that these results are not due to compositional changes in the pool of searching workers, nor are they due to movements of workers in and out of the labor force. He too concluded that the results contradict the conventional wisdom of the last fifteen years. If one wants to understand fluctuations in unemployment, one must understand fluctuations in the transition rate from unemployment to employment, not fluctuations in the separation rate.

This challenging view has met with a number of replies. Davis (2005) showed that understating the cyclical variation in the separation rate would lead to an overstatement of the cyclical variation in the job finding rate. Relying on fluctuations mostly in the job finding rate to explain labor market outcomes leads to counter-factual implications. Simulating a drop in the job-finding rate as in a recession but with no change in the separation rate, he shows (see his Figure 2.17 and the discussion on pp. 142-144) the following: the E to U flow rises too little relative to the data and the U to E flow falls too much relative to the data. The way to obtain results in accordance with the data is to posit a sharp rise in the separation rate. Fujita and Ramey (2008) construct a decomposition of unemployment variability which contradicts Shimer's (2007) conclusions. They find that separation rates are highly countercyclical under alternative cyclical measures and filtering methods and that fluctuations in separation rates contribute substantially to overall unemployment variability. Elsby et al (2007) show that even with Shimer's (2007) methods and data there is an important role for countercyclical inflows into unemployment. Their conclusions are further strengthened when they refine Shimer's methods of correcting CPS labor force series for the 1994 redesign and for time aggregation and undertake a disaggregated analysis.

Model Performance. In terms of the fit of the search and matching model, Merz (1995), Andolfatto (1996), and den Haan et al (2000) have shown that the model is able to capture salient features of the data and improve on the performance of the standard RBC model. Mortensen and Pissarides (1994) extended the basic Pissarides (1985) model to cater for endogenous separations in order to capture the stylized facts on the importance of job destruction.

However, subsequently, a number of papers claimed that the model does not fit the data well. In particular:

(i) Cole and Rogerson (1999) found that the model can account for business cycle facts only if the average duration of unemployment is relatively high (9 months or longer), substantially longer than in the actual data.

(ii) Fujita (2004) presented empirical tests showing that vacancies are much more persistent in the data than the low persistence implied by the model.

(iii) Veracierto (2008) has shown that the model fails to simultaneously account for the observed behavior of employment, unemployment, and out of the labor force worker pools. In particular, employment fluctuates as much as the labor force while in the data it is three times more variable, unemployment fluctuates as much as output while in the data it is six times more variable, and unemployment is acyclical while in the data it is strongly countercyclical. An underlying reason is that search decisions respond too little to aggregate productivity shocks.

(iv) Costain and Reiter (2008) argued that in a RBC model with matching, procyclical employment fluctuations occur when match productivity rises in booms. At the same time an increase in unemployment benefits negatively affects employment by reducing the match surplus. They then show that the standard model implies a close relationship between the two, but that this is strongly at odds with data. To reproduce business cycle fluctuations, matching must be quite elastic with respect to the surplus; but to reproduce the observed effects of unemployment benefits policies, matching must be, at the same time, more inelastic.

(v) In a highly influential paper, Shimer (2005) showed that the standard search and matching model can explain only a small fraction of cyclical fluctuations in the labor market, most notably those of unemployment and vacancies. The key reason for this result is that the standard model assumes that wages are determined by Nash bargaining, which in turn implies that wages are "too flexible." Thus, for example, following a positive productivity shock wages increase, absorbing the shock and thereby dampening the incentives of firms to create new jobs.

These critiques have received some responses. To cite some papers in this growing literature, Mortensen and Nagypal (2007) show that a modified version of the model can explain the magnitude of the empirical relationship between the vacancy–unemployment ratio and labor productivity when wages are the outcome of a strategic bargaining game and when the elasticity of the matching function and the opportunity cost of a match are set at reasonable values. The modified model also explains almost two thirds of the volatility in the ratio relative to that of productivity when separation shocks are taken into account, as well as the strong negative correlation between vacancies and unemployment. Pissarides (2007) summarizes microeconometric evidence on wages in new matches and shows that the key model elasticities are consistent with the evidence. He concludes that explanations of the 'Shimer puzzle' have to preserve the cyclical volatility of wages. Hagedorn and Manovskii (2008) propose a new way to calibrate the parameters of the model and find that the model is consistent with the key business cycle facts. In particular, it generates volatilities of unemployment, vacancies, and labor market tightness that are very close to those in the data. They do so using a relatively low value for the workers' bargaining parameter and a value of non-market activity that is fairly close to market productivity.

Data and Theory. There is a link between the afore-cited data issues and the theoretical issues. According to the Shimer-Hall view the main issue for the study of business cycles is explaining the pro-cyclicality and volatility of the job finding rate, as the separation rate is almost constant. The job finding rate depends on market tightness. The model, therefore, needs to account for the cyclical behavior of market tightness, but it is unable to do so in its standard form. This view needs to be contrasted with the earlier view, which posited that separations from employment are at least as important, if not more important, than hirings, both need to be explained, and the model is able to account for the major facts.

3 U.S. Data

In this section I build on the findings in Yashiv (2007b) to re-examine the data properties of U.S. labor market dynamics.

3.1 Labor Market Dynamics: Basic Equations

The dynamic equations of the labor market recognize the fact that in addition to the official pool of unemployed workers, to be denoted U, there is another relevant pool of non-employed workers – the 'out of the labor force' category, to be denoted N, and that there are substantial flows between the latter and the employment pool E.

The evolution of employment proceeds according to the following equation

$$E_{t+1} = E_t + M_t^{UE+NE} - S_t^{EU+EN} \tag{1}$$

where E is the employment stock, M^{UE+NE} are gross hiring flows from both unemployment and out of the labor force and S^{EU+EN} are separation flows to these pools. In terms of rates this equation may be re-written as:

$$\frac{E_{t+1}}{E_t} - 1 = \frac{M_t^{UE+NE}}{E_t} - \delta_t^{EU+EN} \tag{2}$$

where $\delta = \frac{S}{E}$ is the separation rate from employment.

A similar equation holds true for unemployment dynamics:

$$U_{t+1} = U_t(1 - p_t^{UE}) + \delta_t^{EU} E_t + F_t^{NU} - F_t^{UN} \tag{3}$$

where U is the unemployment stock, p^{UE} is the job finding rate (moving from unemployment to employment), and $F_t^{NU} - F_t^{UN}$ is the net inflow of workers from out of the labor force, joining the unemployment pool (computed by deducting the gross flow out of unemployment from the gross flow into it).

This can be re-written:

$$\frac{U_{t+1}}{U_t} - 1 = -p_t^{UE} + \delta_t^{EU}\frac{E_t}{L_t}\frac{L_t}{U_t} + \frac{F_t^{NU} - F_t^{UN}}{L_t}\frac{L_t}{U_t} \tag{4}$$

In steady state there is a constant growth rate of unemployment at the rate of labor force growth to be denoted g^L:

$$\frac{U_{t+1}}{U_t} - 1 = g^L \tag{5}$$

Thus the unemployment rate is constant at $\overline{u}$:

$$\overline{u} = \frac{U}{L} \tag{6}$$

The dynamic equation (4) becomes:

$$g^L = -p^{UE} + \delta^{EU}(1-\overline{u})\frac{1}{\overline{u}} + \frac{F^{NU} - F^{UN}}{L}\frac{1}{\overline{u}} \tag{7}$$

Hence steady state unemployment is given by

$$\overline{u} = \frac{\frac{F^{NU}-F^{UN}}{L} + \delta^{EU}}{p^{UE} + g^L + \delta^{EU}} \tag{8}$$

In case there is no labor force growth or workers joining from out of the labor force, i.e., $\frac{F^{NU}-F^{UN}}{L} = g^L = 0$, this becomes:

$$\overline{u} = \frac{\delta^{EU}}{\delta^{EU} + p^{UE}} \tag{9}$$

Noting that $M_t = p_t U_t$ and $\delta_t = \frac{S_t}{E_t}$, the empirical researcher needs data on the stocks U_t and E_t and on the flows M_t and S_t, to investigate the determinants of $\overline{u}$.

Note some implications of these equations::

(i) Taking the whole employment stock, E, as one pool to be explained, it is flows to and from this pool that need to be accounted for. Flows within E (job to job) do not change E itself. In what follows, the term 'separations' will refer to separations from E and 'hires' will refer to hiring into E, and not to separations or hires within E. This is an important distinction, as some studies focused on separation from employment δ^{EU+EN} while others focused on total separations $\delta^{EU+EN+EE}$.

(ii) Another important distinction is between hiring rates $\frac{M^{UE}}{E}$ and job finding rates $p^{UE} = \frac{M^{UE}}{U}$; some studies compared the separation rate from employment δ^{EU} to the former, while others emphasized the comparison to the latter.

(iii) The key variables for understanding the rate of unemployment at the steady state are p^{UE}, δ^{EU}, $\frac{F^{NU}-F^{UN}}{L}$ and g^{L}.

3.2 Data Sources

There are two main sources for U.S. aggregate worker flow data: the CPS and JOLTS, both of the BLS. The CPS, available at http://www.bls.gov/cps/, is a household survey and offers a worker perspective. JOLTS data, available at http://www.bls.gov/jlt/home.htm, are based on a survey of employers. This data-set includes monthly figures for hires, separations, quits, layoffs, and vacancies.

The CPS is the main basis for the data sets to be analyzed below. These data were computed and analyzed by Blanchard and Diamond (1989, 1990), Ritter (1993), Bleakley, Ferris and Fuhrer (1999),[2] Fallick and Fleischmann (2004), and Shimer (2007).[3] Note that what is done below is not the analysis of the raw CPS data but rather the analysis of the computed data, i.e., the computed gross flows, based on CPS, as undertaken by the cited authors.

JOLTS data were reported and discussed by Hall (2005). Wherever relevant, I take the JOLTS data from the BLS website.

3.3 Measurement Issues

The CPS is a rotating panel, with each household in the survey participating for four consecutive months, rotated out for eight months, then included again for four months. With this structure of the survey, not more than three-quarters of survey respondents can be matched, and typically the fraction is lower because of survey dropouts and non-responses. Using these matched records, the

[2] Updated further till 2003:12.

[3] A summary of data sources and a discussion of them is to be found in Farber (1999), Davis and Haltiwanger (1998,1999), Fallick and Fleischmann (2004), and Davis, Faberman, and Haltiwanger (2006).

gross flows can be constructed. However, there are various problems that need to be addressed when doing so. Thus, while such flows have been tabulated monthly from the CPS since 1949, the BLS has not published them because of their "poor quality." More specifically, missing observations and classification error were noted. These issues are discussed in detail in Abowd and Zellner (1985) and in Poterba and Summers (1986), who offer corrective measures. Additional issues involve methods of matching individuals across months, weighting individuals, aggregation across sectors and over time, survey methodology changes (in particular the 1994 CPS redesign), and seasonal adjustment. The above two studies, as well as the five studies which data are examined here, offer extensive discussion.

3.4 Why data series may differ

In the next sub-section I present an analysis of the afore-cited five data sets, computed by different authors on the basis of raw CPS data. They turn out not to be the same. Why so? The preceding discussion makes it clear that there are various measurement issues that need to be treated. It is evident that if treatment methods vary then the resulting series will differ. The discussion in Bleakley et al (1999, pages 72-76) gives important details about these adjustments. As key examples, consider the following points which emerge from this discussion:

Adjustments are substantial. The Abowd-Zellner adjustments for misclasssification substantially reduce the transitions between labor market states. The N - E flows have the largest reduction, almost 50 percent.

Application of adjustment methods may vary. The different authors have not used the same corrections of the data. One striking example is the use of fixed Abowd-Zellner adjustment factors despite evidence of time variation in these factors (see the discussion in Bleakley et al (1999) page 75).[4] Another example is the use by Bleakley et al (1999) of additional adjustments, dealing with the 1994 CPS redesign.

Seasonal adjustment may vary. The gross flows data exhibit very high seasonal variation (see for example the discussion of Tables 1 and 2 in Bleakley et al (1999)). The methodology

[4] This discussion makes it clear that Abowd-Zellner adjustments depend on time-varying factors, with the possible implication that they will be applied differently by different authors.

of seasonally adjusting the series differs across studies: Blanchard and Diamond (1990) use the Census Bureau X11 program. Ritter (1993) also seasonally adjusts using the X-11 procedure but further smooths using a five-month centered moving average. Bleakley et al (1999) note the use of regressions on monthly dummies as well as the X11 methodology. Fallick and Fleischmann (2004) use the newer Census Bureau X12 seasonal adjustment program. Shimer (2007) uses a ratio-to-moving average technique.

Hence, even though the data source may be the same, the resulting series may differ depending upon the differential application of adjustments.

3.5 Key Moments of the Gross Flows Data

The key findings are reported in Table 1 and Figures 1-6.

Table 1 and Figures 1-6

The following are the emerging points:

Flows from Unemployment.

a. The monthly hiring rate ($\frac{M^{UE}}{E}$) is around 1.5%-1.7%, with a standard deviation of 0.1%-0.3%. Four series give a very similar picture. The series from Shimer (2007), with a 2% mean, is somewhat higher than the four others. This is probably due to the fact that he captures more transitions by correcting for time aggregation.

b. The monthly job finding rate ($p^{UE} = \frac{M^{UE}}{U}$) is around 25%-32% on average. The series from Shimer (2007), with a 32% mean, is again somewhat higher than the four others. These numbers imply quarterly rates of around $60\% - 70\%$. The average monthly volatility of this rate is around 3%-6%.

Flows from Out of the Labor Force. There seem to be two data sets here: Blanchard and Diamond (1989) and Bleakley et al. (1999), report mean hiring rates of 1.3%-1.5% and standard deviation of 0.1%-0.3%. The other two data sets span different sample periods but indicate mean hiring rates of 2.5%-2.9% and standard deviation of 0.2% or 0.4%.

Total Hires. The total hires flows reflect the differences between the data sets as discussed above. There is one addition, though, and that is JOLTS. While it has a mean rate of 3.2%

and standard deviation of 0.2%, similar to Bleakley, Ferris and Fuhrer (1999), it has a negative correlation of -0.22 with the latter series.[5]

Flows from employment to unemployment. The monthly separation rate into unemployment is around 1.3%-1.5% on average for all studies, except Shimer who puts it at 2%, again because of the treatment of time aggregation. The former imply quarterly separation rates of around 4%, while the latter implies 5.9%. Its volatility is around 0.1%-0.3% in monthly terms according to all studies.

Flows from Employment to Out of the Labor Force. The different data sets again seem to suggest different moments: a monthly mean ranging from 1.5% to 3.2% and a standard deviation ranging from 0.2% to 0.5%.

Total Separations. As in the case of total hires, the total separations flows reflect the differences between the data sets discussed above; and, again, there is the addition of the JOLTS data set. The picture that emerges is the following: the mean separation rate ranges from around 3% a month according to three sources to as high as 5% according to Shimer. The standard deviation ranges from a low of 0.15% according to the JOLTS data to as high as 0.47% according to Shimer.

3.6 The Cyclical Behavior of Flows

A key issue in the cited literature is the cyclical properties of these flows. Table 2 reports correlations and relative standard deviations of hiring rates, job finding rates,[6] and separation rates with real GDP.

Table 2

Panel a of the table uses the Bleakley et al. (1999) data with four alternative detrending methods (all on the logged series): first differences, the Hodrick-Prescott (HP) filter with the standard smoothing parameter ($\lambda = 1600$), with a low frequency filter ($\lambda = 10^5$), and the Baxter-King (BK) band-pass filter. Panel b reports the results for the other data sets using the Hodrick-

[5]It should be remarked, though, that there are only 49 overlapping monthly observations for these two series.

[6]Note that it is not obvious what would be a correct measure of aggregate p, i.e. incorporating both p^{UE} and p^{NE}.

Prescott (HP) filter with the standard smoothing parameter ($\lambda = 1600$); computations of the other filters for these data sets are available from the author. Panel c uses the Shimer (2007) data to report cross-correlations.

The table and the figure indicate the following patterns, all with respect to real GDP.

Co-movement. Generally across studies the following holds true:

(i) Hiring rates from unemployment to employment ($\frac{M^{UE}}{E}$) are counter-cyclical, while hiring rates from out of the labor force to employment ($\frac{M^{NE}}{E}$) are pro-cyclical. Summing up the two ($\frac{M^{UE}+M^{NE}}{E}$) yields a flow that is moderately counter-cyclical.

The first result may seem counter-intuitive – flows from unemployment into employment increase in recessions and fall in booms. But note that $M = pU$. The job finding rate p falls and U rises in recessions, as one would expect intuitively. As the latter effect is stronger than the former effect M rises in recessions. Moreover, E falls at those times. Hence $\frac{M}{E}$ rises in recessions.

(ii) Job finding rates from unemployment to employment (p^{UE}) are pro-cyclical.

(iii) Separation rates from employment to unemployment (δ^{EU}) are counter-cyclical, while those from employment to out of the labor force (δ^{EN}) are pro-cyclical. Summing up the two (δ^{EU+EN}) yields a flow that is moderately counter-cyclical.

(iv) The cross correlation analysis of the last panel in Table 3 indicates that these cyclical patterns hold true at leads and lags of up to six months.

Volatility. Across studies the following holds true:

(i) Hiring rates $\frac{M}{E}$, job finding rates p, and separation rates δ are highly volatile, roughly 2 to 4 times the volatility of real GDP.

(ii) Hiring rates from unemployment to employment ($\frac{M^{UE}}{E}$) are less volatile than the corresponding separation flows (δ^{EU}).

(iii) The reverse is true for flows between out of the labor force and employment, i.e., $\frac{M^{NE}}{E}$ is more volatile than δ^{EN}.

(iv) The sum of the hiring flows ($\frac{M^{UE}+M^{NE}}{E}$) is less volatile than the sum of the separation flows (δ^{EU+EN}).

(v) There is no agreement across studies about the relationship between the volatility of the job finding rate p^{UE} and the volatility of the separation rate δ^{EU}. In the Blanchard and Diamond

(1989,1990) and Ritter (1993) data the latter is more volatile than the former across all filtering methods; in the Bleakley, Ferris and Fuhrer (1999) data this is generally so too, but using the 10^5 HP filter they have almost the same volatility; in Fallick and Fleischmann (2004) separations are more volatile than hirings, but under the low frequency HP filter this relation is reversed; the Shimer (2007) data indicate that for most filtering methods the opposite holds true, i.e. p^{UE} is more volatile than δ^{EU}. These inconsistencies may be due to a changing relationship between job finding and separation over time, as it was noted that the UE and EU flows are measured similarly across studies for a given period of time. Note too, that even for the Shimer data the volatility of aggregate job finding p^{UE+NE} is very similar to that of aggregate separations δ^{EU+EN}.

Data interpretation. It is possible to use any data set to substantiate each of the contradictory interpretations discussed above. Two examples may serve to illustrate. To support the earlier view on the importance of separations, one could even use the Shimer (2007) results. Thus, the volatility of δ^{EU} is higher than $\frac{M^{UE}}{E}$ in his data (see Panel b of Table 2) and both have about the same cyclicality under all filtering methods. To support the more recent, Hall-Shimer view on the importance of job finding, one could use the Bleakley, Ferris and Fuhrer (1999) results. Thus the volatility of p^{UE} is higher than the volatility of δ^{EN} or δ^{EU+EN} and the cyclicality of job finding is stronger under all filtering methods. Why, then, the debates? This is mostly due to the fact that researchers have looked at different objects, as illustrated in these two examples. There is a difference between the behavior of the hiring rate $\frac{M}{E}$ and the job finding rate p and there is a difference between looking at narrower flows (such as flows between U and E) and wider ones (such as adding flows between N and E or E to E flows). The latter point is manifested in the declining volatility and cyclicality of the separation rate, as more flows out of employment are considered. This is so because the cyclical behavior of the different components of the separation rate move in opposite direction, a point emphasized by Davis (2005). The key compositional issue is that layoffs are counter-cyclical and quits are pro-cyclical according to many sources of evidence. If, as this evidence suggests, layoffs contribute mostly to the EU flow and quits to the EN and EE flows, then the wider is the separation flow measure, the less volatile and cyclical will it be.

The facts that can be agreed upon are the ones to be explained. I turn now to two versions of the search and matching model to see whether it can explain the facts.

4 The Search and Matching Model: Partial Equilibrium

In this section I build on Yashiv (2006) to look at a partial equilibrium version of the search and matching model, based on Pissarides (1985)[7]. In the next section I look at the general equilibrium version. It turns out that there are advantages to each approach and therefore it is useful to look at both.

4.1 The Model

4.1.1 Basic Set-Up

There are two types of agents: unemployed workers (U) searching for jobs and firms recruiting workers through vacancy creation (V). Firms maximize their intertemporal profit functions with the choice variable being the number of vacancies to open. Each firm produces a flow of output (F), paying workers wages (W) and incurring hiring costs (Γ). Workers and firms are faced with different frictions such as different locations leading to regional mismatch or lags and asymmetries in the transmission of information. These frictions are embedded in the concept of a matching function which produces hires (M) out of vacancies and unemployment, leaving certain jobs unfilled and certain workers unemployed. Workers are assumed to be separated from jobs at a stochastic, exogenous rate, to be denoted by δ. The labor force (L) is growing with new workers flowing into the unemployment pool. The model assumes a market populated by many identical workers and firms. Hence I shall continue the discussion in terms of "representative agents." Each agent is small enough so that the behavior of other agents is taken as given.

4.1.2 Matching

A matching function captures the frictions in the matching process; it satisfies the following properties:

$$\begin{aligned} M_t &= \widetilde{M}(U_t, V_t) \qquad (10) \\ \frac{\partial \widetilde{M}}{\partial U} &> 0, \ \frac{\partial \widetilde{M}}{\partial V} > 0 \end{aligned}$$

[7] For a recent survey of the model see Yashiv (2007a).

Empirical work [see the survey by Petrongolo and Pissarides (2001)] has shown that a Cobb-Douglas function is useful for parameterizing it:

$$M_t = \mu U_t^{\sigma} V_t^{1-\sigma} \tag{11}$$

where μ stands for matching technology. The parameter σ reflects the relative contribution of unemployment to the matching process and determines the elasticity of the hazard rates with respect to market tightness $\frac{V_t}{U_t}$.[8]

4.1.3 Firms

Firms maximize the expected, present value of profits (where all other factors of production have been "maximized out"):

$$\max_{\{V\}} \Pi_0 = \epsilon_0 \left[\sum_{t=0}^{\infty} (\prod_{j=0}^{t} \beta_j) \left[F_t - W_t E_t - \Gamma_t \right] \right] \tag{12}$$

where ϵ is the expectations operator and $\beta_j = \frac{1}{1+r_{t-1,t}}$.

This maximization is done subject to the employment dynamics equation given by:

$$E_{t+1} = (1 - \delta_t) E_t + Q_t V_t \tag{13}$$

The main F.O.C are:[9]

$$\frac{\partial \Gamma_t}{\partial V_t} = Q_t \epsilon_t \Lambda_{t+1} \tag{14}$$

[8] The hazard rates – P, the worker probability of finding a job, and Q, the firm's probability of filling the vacancy – are derived as follows:

$$P_t = \frac{M_t}{U_t} = \mu (\frac{V_t}{U_t})^{1-\sigma}$$
$$Q_t = \frac{M_t}{V_t} = \mu \left(\frac{V_t}{U_t} \right)^{-\sigma}$$

[9] Other F.O.C are the flow constraint (1) and a transversality condition.

$$\Lambda_{t+1} = \epsilon_t \left[\beta_{t+1}\left[\frac{\partial F_{t+1}}{\partial E_{t+1}} - \frac{\partial \Gamma_{t+1}}{\partial E_{t+1}} - \frac{\partial (W_{t+1}E_{t+1})}{\partial E_{t+1}}\right]\right] + \epsilon_t \left[\beta_{t+2}(1-\delta_{t+2})\Lambda_{t+2}\right] \tag{15}$$

The first, intratemporal condition (equation 14) sets the marginal cost of hiring $\frac{\partial \Gamma_t}{\partial V_t}$ equal to the expected value of the multiplier times the probability of filling the vacancy. The second, intertemporal condition (equation 15) sets the multiplier equal to the sum of the expected, discounted marginal profit in the next period $\epsilon_t \left[\beta_{t+1}\left[\frac{\partial F_{t+1}}{\partial E_{t+1}} - \frac{\partial \Gamma_{t+1}}{\partial E_{t+1}} - \frac{\partial (W_{t+1}E_{t+1})}{\partial E_{t+1}}\right]\right]$ and the expected, discounted (using also δ) value of the multiplier in the next period $\epsilon_t \left[\beta_{t+2}(1-\delta_{t+2})\Lambda_{t+2}\right]$.[10]

Hiring costs refer to the costs incurred in all stages of recruiting: the cost of posting, advertising and screening – pertaining to all vacancies (V), and the cost of training and disrupting production – pertaining to actual hires (QV). For the functional form I use a power function formulation. This modelling relates to the same rationale being used in the capital adjustment costs/Tobin's Q literature. It emerged as the preferred one − for example as performing better than polynomials of various degrees − in structural estimation of this model reported in Yashiv (2000a,b) and in Merz and Yashiv (2007). The former studies used an Israeli data-set that is uniquely suited for such estimation with a directly measured vacancy series that fits well the model's definitions. The latter study used U.S. data. Formally this function is given by:

$$\Gamma_t = \frac{\Theta}{1+\gamma}\left(\frac{\phi V_t + (1-\phi)Q_t V_t}{E_t}\right)^{\gamma+1} F_t \tag{16}$$

Hiring costs are a function of the weighted average of the number of vacancies and the number of hires. They are internal to production and hence are proportional to output. Note that Θ is a scale parameter, ϕ is the weight given to vacancies as distinct from actual hires, and γ expresses the degree of convexity.

The function is linearly homogenous in V, E and F. It encompasses the cases of a fixed cost per vacancy (i.e. linear costs, $\gamma = 0$) and increasing costs ($\gamma > 0$). Note, in particular, two

[10] Note that because I postulate that Γ depends on E (see below), the net marginal product for the firm depends on E. This marginal product is part of the match surplus bargained over, and therefore part of the wage solution discussed below. Hence the term $\frac{\partial W_{t+1}}{\partial E_{t+1}}$, usually absent, is not zero in this formulation.

special cases: when $\gamma = 0$ and $\phi = 1$, I get $\Gamma_t = \Theta V_t \frac{F_t}{E_t}$, which is the standard specification in much of the literature. When $\gamma = 1$, I get the quadratic formulation $\Gamma_t = \frac{\Theta}{2}(\frac{\phi V_t + (1-\phi)Q_t V_t}{E_t})^2 F_t$, which is analogous to the standard formulation in "Tobin's q" models of investment where costs are quadratic in $\frac{I}{K}$.

4.1.4 Wages

In this model, the matching of a worker and a vacancy against the backdrop of search costs, creates a joint surplus relative to the alternatives of continued search. The prototypical search and matching model derives the wage (W) as the Nash solution of the bargaining problem of dividing this surplus between the firm and the worker [see the discussion in Pissarides (2000, Chapters 1 and 3)]. Note that I follow the prototypical model in the way it models wage setting in general, and in the specific form of wage bargaining in particular.

Formally this wage is:

$$W_t = \arg\max (J_t^N - J_t^U)^{\xi} (J_t^F - J_t^V)^{1-\xi} \tag{17}$$

where J^N and J^U are the present value for the worker of employment and unemployment respectively; J^F and J^V are the firm's present value of profits from a filled job and from a vacancy respectively; and $0 < \xi < 1$ reflects the degree of asymmetry in bargaining.

Using the approach of Cahuc, Marque and Wasmer (2004) to solve (17) taking into account the fact that $\frac{\partial W_{t+1}}{\partial E_{t+1}} \neq 0$, the wage is given by:[11]

$$\begin{aligned} W_t &= \xi \left(\begin{array}{c} \alpha A \left(\frac{K_t}{E_t}\right)^{1-\alpha} \left[\frac{1}{1-(1-\alpha)\xi} + \Theta(\frac{\phi V_t + (1-\phi)Q_t V_t}{E_t})^{\gamma+1} \frac{1-\alpha+\gamma}{(1+\gamma)\alpha(1-\xi(1+(1-\alpha)+\gamma))}\right] \\ +P_t \Lambda_t \end{array} \right) \\ &\quad +(1-\xi) b_t \end{aligned} \tag{18}$$

where b_t is the income of the unemployed, such as unemployment benefits. I will posit $b_t = \tau W_t$, where τ is the replacement ratio.[12]

[11] The solution entails postulating the asset values of a filled job and of a vacant job for the firm and the asset values of employment and unemployment for the worker in (17).

[12] Below I shall use $\eta = \frac{\xi}{(\xi + (1-\xi)\tau)}$

I will also use the concept of the labor share in income:

$$s_t = \frac{W_t}{\frac{F_t}{E_t}} \tag{19}$$

4.1.5 Equilibrium

The stocks of unemployment and employment and the flow of hiring emerge as equilibrium solutions. Solving the firms' maximization problem yields a dynamic path for vacancies; these and the stock of unemployment serve as inputs to the matching function; matches together with separation rates and labor force growth change the stocks of employment and unemployment.

This dynamic system may be solved for the five endogenous variables V, U, M, E and W given initial values U_0, E_0 and given the path of the exogenous variables. As noted above, this is a partial equilibrium model. The exogenous variables include the worker's marginal product, the discount factor, the labor force, and the separation rate.

In the following sub-sections I solve explicitly for a stochastic, dynamic equilibrium using a stochastic structure for the exogenous variables.

4.2 Methodology

I use a log-linear approach, transforming the non-linear problem into a first-order, linear, difference equations system through approximation and then solving the system using standard methods. To abstract from population growth, in what follows I cast all labor market variables in terms of rates out of the labor force L_t, denoting them by lower case letters. Productivity growth is captured by the evolution of A, which enters the model through the dynamics of $\frac{F_t}{E_t}$, so I divide all variables by the latter. This leaves a system that is stationary and is affected by shocks to labor force *growth,* to productivity *growth,* as well as to the interest rate and to the job separation rate, to be formalized below.

The model has four exogenous variables. These are productivity growth ($G^X = \frac{\frac{F_{t+1}}{E_{t+1}}}{\frac{F_t}{E_t}}$), labor force growth ($g^L = \frac{L_{t+1}}{L_t}$), the discount factor ($\beta$) and the separation rate (δ). These affect dynamics as follows: productivity growth G^X raises the match surplus; the discount rate β (related to the rate of interest) and the separation rate δ are components of the relevant discount rate used in computing the present value of the match. Empirical testing reveals that g^L can be modelled as white noise around a constant value. When I tried to add it as a stochastic variable to the framework below the results were not affected, so I treat it as a constant. It is the other three variables that inject shocks into this system. I do not formulate the underlying shocks structurally. Instead, I postulate that they follow a first-order VAR (for each variable Y, I use the notation $\widehat{Y}_t = \frac{Y_t - Y}{Y} \approx \ln Y_t - \ln Y$ where Y is the steady state value, so all variables are log deviations from steady state):

$$\begin{bmatrix} \widehat{G}^X_{t+1} \\ \widehat{\beta}_{t+1} \\ \widehat{\delta}_{t+1} \end{bmatrix} = \Pi \begin{bmatrix} \widehat{G}^X_t \\ \widehat{\beta}_t \\ \widehat{\delta}_t \end{bmatrix} + \Sigma \tag{20}$$

I use reduced-form VAR estimates of the data to quantify the coefficient matrix Π and the variance-covariance matrix of the disturbances Σ. Thus the current model is consistent with both RBC-style models that emphasize technology shocks as well as with models that emphasize other shocks. Note also that the shocks may interact through the off-diagnonal elements in Π and Σ.

In the non-stochastic steady state the rate of vacancy creation is given by:

$$\Theta\,(\phi + (1-\phi)Q)\,(\frac{\phi V + (1-\phi)QV}{E})^{\gamma} = Q\frac{G^X\beta}{[1-(1-\delta)G^X\beta]}\pi \tag{21}$$

The LHS are marginal costs; the RHS is the match asset value. It is the probability of filling a vacancy (Q) times the marginal profits accrued in the steady state. The latter are the product of per-period marginal profits π and a discount factor $\frac{G^X\beta}{1-G^X\beta(1-\delta)}$ that takes into account the real rate of interest, the rate of separation and productivity growth.

As discussed above, steady state unemployment is given by

$$u = \frac{\frac{F^{NU}-F^{UN}}{L} + \delta^{EU}}{p^{UE} + g^L + \delta^{EU}} \tag{22}$$

I log-linearly approximate the F.O.C in the neighborhood of this steady state. The resulting system is a first-order, linear, difference equation system in the state variable $\widehat{e}$ and the co-state $\widehat{\lambda}$ with three exogenous variables, $\widehat{G}^X$, $\widehat{\beta}$ and $\widehat{\delta}$. The matrices of coefficients are defined by the parameters $\Theta, \gamma, \phi, \mu, \sigma$ and η and by the steady state values of various variables. The solution of this system enables me to solve for the control variable − vacancies, and for other variables of interest, such as unemployment, hires, the matching rate, and the labor share of income.[13]

4.3 Calibration

There are three structural parameters that are at the focal point of the model and that reflect the operation of frictions. These are the matching function parameter σ (elasticity of unemployment), the wage parameter ξ, and the hiring function convexity parameter γ.

For σ I use Blanchard and Diamond's (1989) estimate of 0.4. Structural estimation of the model using U.S. corporate sector data in Merz and Yashiv (2007) indicates a value of γ, the convexity parameter of the hiring cost function, around 2, i.e. a cubic function ($\gamma+1 = 3$) for hiring costs. These costs fall on vacancies and on actual hires, with ϕ being the weight on the former. I follow the estimates in Yashiv (2000a) and set it at 0.3. The wage depends on the asymmetry of the bargaining solution (ξ). Rather than imposing it, I solve it out of the steady state relations.

For the values of the exogenous variables I use sample average values. Calibration of Q, the matching rate for vacancies, is problematic as there are no wide or accurate measures of vacancy durations for the U.S. economy. Using a 1982 survey, Burdett and Cunningham (1998) estimated hazard functions for vacancies both parametrically and semi-parametrically finding that the general form of the hazard function within the quarter is non-monotonic; based on their estimates the quarterly hazard rate should be in the range of $0.8 - 1$. I thus take $Q = 0.9$ which is also the value used by Merz (1995) and Andolfatto (1996). This implies a particular steady state value for the vacancy rate (v). I use the average of the labor share in income s which is 0.58.

With the above values, I solve the steady state relations for the steady state vacancy rate v, the hiring cost scale parameter Θ, the matching function scale parameter μ, and the wage parameter ξ. I can then solve for the steady state values of market tightness $\frac{v}{u}$, the worker hazard rate P, per period profits π and the match asset value λ.

The following table summarizes the calibrated values.

Table 3

[13] I thank Craig Burnside for generously sharing his Gauss simulation program and for very useful advice.

The data appendix specifies definitions and sources.

4.4 Model-Data Fit

I now turn to examine the performance of the model. Table 4 shows the moments implied by the model and those of the data.

Table 4

The following conclusions can be drawn:

Persistence. The model captures the fact that u, m and s are highly persistent. The model tends to somewhat overstate this persistence.

Volatility. The model captures very well the volatility of employment and unemployment. Hiring volatility is understated by the model. As to the labor share, the model substantially overstates its volatility.

Co-Movement. The counter-cyclical behavior of hiring and the pro-cyclical behavior of the worker job finding rate are well captured. But the behavior of the labor share is not captured: while in the data it is basically a-cyclical and co-varies moderately with the hiring rate, it is strongly pro-cyclical in the model and has a strong negative relationship with hiring.

Overall fit. The model captures the persistence, volatility, and some of the co-movement in the data. The major problem concerns the labor share in income which is not well captured.

I turn now to look at the mechanism driving this model-data fit.

4.5 The Underlying Mechanism

The natural question to ask now is what underlies the fit and how it differs from studies like Shimer (2005), which had reached different conclusions. In order to understand the essential mechanism in operation, I analyze the non-stochastic steady state and the stochastic dynamics.

4.5.1 The Non-Stochastic Steady State

Consider the following steady-state equations, the first of which is a re-writing of (21), and the second – equation (22) above – being the equality of unemployment inflows and outflows, usually referred to as the Beveridge curve:

$$\Theta\widetilde{Q}(\frac{\widetilde{Q}v}{e})^{\gamma} = Q\Phi\pi \tag{23}$$

where $\widetilde{Q} = \phi + (1-\phi)Q$ and $\Phi = \frac{G^X\beta}{[1-(1-\delta)G^X\beta]}$.

$$u = \frac{\frac{F^{NU}-F^{UN}}{L} + \delta^{EU}}{\mu(\frac{v}{u})^{1-\sigma} + g^L + \delta^{EU}} \tag{24}$$

Equation (23) shows the vacancy creation decision as an optimality condition equating the marginal costs of hiring (the LHS) with the asset value of the match (the RHS). It is clear that the responsiveness of vacancies (v) depends on the elasticity parameter γ of the hiring cost function. The RHS is the asset value of the match. This value can vary because per period profits π vary, because the discount factor Φ varies, or because the matching hazard Q varies. Profits may vary because of changes in the match surplus or changes in the sharing of the surplus, with a key parameter being ξ. Changes in the discount factor Φ can happen because of changes in productivity growth (G^X), changes in the discount factor (β), or changes in the separation rate (δ). Changes in the matching rate Q are predicated on changes in market tightness $\frac{V}{U}$.

The following ingredients are therefore essential:

(i) The *formulation and shape of the hiring costs function* determining the LHS of equation (23) i.e., the marginal cost function, where γ is a key parameter.

(ii) The formulation of the *match surplus* – this depends both on the data used and on all key parameters of the model.

(iii) the *surplus sharing rule*, where ξ is the key parameter.

(iv) the *discounting* of the match surplus – here the data used (for G^X, β and δ) and their stochastic properties are key.

Consider now the three formulations of hiring costs, depending upon the value of γ. The 'classic' formulation in the literature posits $\gamma = 0$ (and $\phi = 1$) so the LHS of equation (23) is given by:

$$\Theta\widetilde{Q}(\frac{\widetilde{Q}v}{e})^{\gamma} = \Theta\frac{f_t}{e_t}$$

Hence marginal vacancy costs in terms of average productivity are a constant Θ.

Based on empirical work (Merz and Yashiv (2007)), the current formulation is $\gamma = 2$ and $0 < \phi < 1$, so the LHS of equation (23) is given by:

$$\Theta\widetilde{Q}(\frac{\widetilde{Q}v}{e})^{\gamma} = \Theta\left[\phi + (1-\phi)Q_t\right]^3 \left[\frac{v_t}{e_t}\right]^2 \frac{f_t}{e_t}$$

Marginal costs are a function of both vacancies and hires and are quadratic in the vacancy rate.

There is an intermediate case $\gamma = 1$ and $0 < \phi < 1$, so the LHS of equation (23) is given by:

$$\Theta\widetilde{Q}(\frac{\widetilde{Q}v}{e})^{\gamma} = \Theta\left[\phi + (1-\phi)Q_t\right]^2 \left[\frac{v_t}{e_t}\right] \frac{f_t}{e_t}$$

Note that these three formulations are not just expressions of different degrees of convexity; they also imply different dependencies on vacancy rates and on the matching hazard.

Figure 7 plots equation (23) in $u - v$ space for these three cases, namely $\gamma = 0, 1$ and 2.

Figure 7

The intuition for these shapes is as follows: for the linear $\gamma = 0$ case, the RHS of equation (23) depends on market tightness $\frac{v}{u}$, but the LHS does not. Hence when u rises (for whatever reason), ceteris paribus, v rises too and the curve is upward sloping. The rise in u causes a decline in the job finding rate p and so wages decline, profits rise and vacancy creation rises. When $\gamma > 0$ while the afore-going consideration holds true, there is an additional one which is quantitatively stronger. As u rises, e falls. On the LHS this means that v falls, ceteris paribus. The reason is that as the employment stock falls, the firm will want to open fewer vacancies for a given present value of profits (costs depend on the vacancy rate). Because the latter effect on costs is stronger than the former effect on profits, the curve in the $\gamma = 1$ or 2 cases is downward sloping.

Now consider a rise in the separation rate, which is part of the discount factor Φ. Figure 8 shows the change in steady state using both equation (23) and equation (24). Panel a shows the $\gamma = 0$ case and panel b the $\gamma = 2$ case.

Figure 8

In both panels, the curve of equation (23) moves relatively little, in line with the arguments posited by Shimer (2005). But the Beveridge curve equation (24) moves substantially. The results of panel (a), the $\gamma = 0$ case, show that v rises with u and market tightness $\frac{v}{u}$ changes little. The results of panel (b), the $\gamma = 2$ case, show that v falls while u rises and that market tightness $\frac{v}{u}$ declines. These results help explain why the standard models (with $\gamma = 0$) have obtained a counterfactual positive relationship between u and v and little movement in market tightness $\frac{v}{u}$. Note that the latter determines the job finding rate p and the matching rate Q. Likewise, this analysis helps explain why the current results fit the data better.

I turn now to the stochastic dynamics.

4.5.2 Stochastic Dynamics

In order to see how the same elements affect the dynamics, I undertake some counterfactual simulations, reported in Table 5.[14]

Table 5

Looking at the convexity of hiring costs (parameterized by γ), the table implies that values of γ determine the persistence and volatility of vacancy creation. The latter then influences the second moments of matching, and consequently the moments of unemployment and employment. To see this, panel (a) of the table presents the outcomes when γ is set to zero, i.e., postulating linear hiring costs. The table shows that when moving from convex ($\gamma = 2$) to linear costs ($\gamma = 0$), all the persistence statistics decline, getting further away from the data; employment volatility falls from the data-consistent 0.021 (in log terms) to 0.015, (and likewise for unemployment); wages become counterfactually more volatile; hiring and separation rates become more disconnected and

[14] Note that the simulations pertain to the full stochastic dynamic system, not only the steady state.

job finding rates become less pro-cyclical. The relationship between u and v, the Beveridge curve, turns positive, and market tightness $(\frac{v}{u})$ volatility falls by a half. The only good point is that hiring volatility comes closer to the data.

The other key element discussed above is the role played by the match separation rate δ. As it is a variable with a relatively high mean, it is the main determinant of the relevant discount factor Φ; as it has relatively high volatility and persistence, it makes the present value of the match volatile and persistent. This in turn engenders the volatility and persistence of vacancies, hiring, and unemployment. To see this point consider panel (b) of Table 5, where, in the column labeled counterfactual 1, the AR coefficient of δ is reduced to 0.1, counterfactually. The change in the moments is substantial: the persistence of all variables falls from 0.98 to 0.55−0.76 and the volatility of all variables is reduced so that standard deviations are 2%-5% of their benchmark, actual values. The co-movement statistics weaken: most of the co-movement relations weaken moderately, and the negative co-movement relations of the labor share with the hiring rate and of unemployment with vacancies weaken substantially. I reset the persistence to its actual value, and, in the column labeled counterfactual 2, I set the variance and co-variance of δ to zero. This dramatically lowers the persistence, the volatility, and the co-movement statistics of all the variables.

Next, I examine whether the interest rate has a similar effect via β. The column labeled counter-factual 3 sets its variance and co-variance to zero but this change hardly has any effect.

Finally, in panel c, I combine both a linear hiring cost function ($\gamma = 0$) and zero variance and co-variance for β and δ. The results are negative auto-correlation statistics, very low volatility, weaker co-movement, and a positive, rather than negative, correlation between u and v. Comparing panel (c) to panels (a) and (b), one can see that allowing no variance for δ is the dominant effect on all moments.

Thus the performance of the model hinges to a large extent on the formulation of γ and on the stochastic properties of δ. The dynamic analysis has shown that the lack of fit in part of the literature is due to the use of a linear hiring cost function ($\gamma = 0$) instead of a convex one ($\gamma = 2$ here), and due to different stochastic properties assigned to the separation rate δ. Other elements of the model play a smaller role. The wage parameter ξ basically has a scale effect on per period profits and hence on the scale of match asset values. It therefore affects the value of the variables at the steady state but does not affect the dynamics, as it does not affect the response of vacancy creation to asset values. The matching function parameter σ, that does have this 'elasticity' type of effect, has a range of possible variation that is much smaller than the variation in values of γ. For example, a reasonable change in σ would be 0.1 or 0.2 relative to the benchmark value (which is 0.4), but a move from linear ($\gamma = 0$) to cubic ($\gamma = 2$) costs is a change of 2 in the value of γ. The interest rate and the rate of productivity growth in their turn play a much smaller role than the separation rate in discounting future values. While δ has a sample mean of 8.6% and a standard deviation of 0.8%, the rate of productivity growth ($G^X - 1$) has a sample mean of 0.4% and standard deviation of 0.6%. The rate of interest ($\frac{1}{\beta} - 1$) has a sample mean of 1.4% and a relatively high standard deviation, 5.5%, but as shown in panel (b) of Table 5 it does not play a significant role.

5 The Search and Matching Model: General Equilibrium

In this section I present a formulation of a DSGE model with search and matching and examine its performance.

5.1 Model

Following the implementation by Den Haan, Ramey, and Watson (2000) and Krause and Lubik (2007) of the Mortensen and Pissarides (1994) model, the following elements and equations are added to the partial equilibrium model presented above or modify some of its elements.

5.1.1 Environment

There is a continuum of infinitely-lived households, which maximize an intertemporal utility function via choice of consumption (C). There is a continuum of identical firms, which maximize the discounted value of expected profits via the choice of job vacancies and threshold productivity. Hence the discussion will be in terms of a representative household and a representative firm. Within the firm there is a continuum of jobs. Productivity has an aggregate component, evolving according to an AR1 process, and a job-specific component. The latter is drawn each period from a time-invariant distribution (with density $g(a)$ and cdf $G(a)$). Workers are assumed to be separated from jobs at a stochastic rate; the latter has an exogenous part, to be denoted by δ^x, and an endogenous part δ^n. δ^n is the result of the existence of an optimal threshold $\underline{a_t}$ for job specific productivity, below which the job and the worker separate.

5.1.2 Households

Households maximize utility:

$$\max_{C} \epsilon_0 \sum_{t=0}^{\infty} \beta^t U(C_t) \tag{25}$$

subject to the budget constraint:

$$C_t + B_t = W_t E_t + b_t U_t + R_{t-1} B_{t-1} - T_t + \Pi_t \tag{26}$$

where ϵ is the expectations operator, C is consumption, β is a discount factor, B is the stock of debt in real terms, bearing gross interest R, WE is labor income (elaborated below), bU is the income of unemployed household members u, which can be thought of as total output of a home production sector with $b > 0$, T are taxes, and Π are firm profits (owned by households).

The F.O.C. is:

$$U_{C_t} = \beta R_t \epsilon_t U_{C_{t+1}} \tag{27}$$

In what follows I shall use the notation:

$$\lambda_t \equiv U_{C_t}$$

5.1.3 Firms

Firms maximize profits:

$$\max_{\{V,\underline{a}\}} \Pi_0 = \epsilon_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left[F_t - W_t E_t - \Gamma_t\right] \tag{28}$$

subject to

$$E_{t+1} = (1-\delta_t)E_t + Q_tV_t \tag{29}$$

The F.O.C are:

$$\frac{\partial \Gamma_t}{\partial V_t} = Q_t\beta\epsilon_t\frac{\lambda_{t+1}}{\lambda_t}\left[\begin{array}{c} \frac{\partial F_{t+1}}{\partial E_{t+1}} - \frac{\partial \Gamma_{t+1}}{\partial E_{t+1}} - \frac{\partial (W_{t+1}E_{t+1})}{\partial E_{t+1}} \\ +(1-\delta_{t+2})\frac{\frac{\partial \Gamma_{t+1}}{\partial V_{t+1}}}{Q_{t+1}} \end{array}\right] \tag{30}$$

$$\frac{\partial F_t}{\partial \underline{a_t}} - \frac{\partial \Gamma_t}{\partial \underline{a_t}} - \frac{\partial (W_tE_t)}{\partial \underline{a_t}} = \epsilon_t\Lambda_{t+1}\left[E_t\frac{\partial \delta_t}{\partial \underline{a_t}}\right] \tag{31}$$

5.1.4 Wage Determination

The Nash wage solution is given by:

$$W(a_t) = \arg\max(J_t^E - J_t^U)^{\xi}(J_t^F - J_t^V)^{1-\xi} \tag{32}$$

which works out to be:

$$\begin{aligned} W(a_t) \quad &= \quad \chi_t\left[\frac{\partial F_t}{\partial E_t} - \frac{\partial \Gamma_t}{\partial E_t} - E_t\frac{\partial W_t}{\partial E_t}\right] + \chi_tP_t\Lambda_t \\ &\quad + (1-\chi_t)\, b_t \\ &\quad \chi_t = \frac{\xi}{(\xi + (1-\xi)\,\tau)} \end{aligned} \tag{33}$$

postulating that $b_t = \tau W_t$.

5.1.5 Functional Forms

For functional forms the following will be used:

CRRA utility defined over consumption.

$$U(C_t) = \frac{C_t^{1-\omega}}{1-\omega}$$

The separation rate is now given by:

$$\delta_t = \delta_t^x + (1-\delta_t^x)\delta_t^n \tag{34}$$
$$\delta_t^n = G(\underline{a_t})$$

Production embeds both aggregate productivity and idiosyncratic productivity as follows. Each worker-job pair in firm i job j produces:

$$\widetilde{f}_{ijt} = A_t a_{ijt} \tag{35}$$

Total output of firm i (across jobs) is given by:

$$f_{it} = A_t e_{it} \int_{\underline{a_t}}^{\infty} a_t \frac{g(a_t)}{1-G(\underline{a_t}))} da_t$$

Total output in the economy is given by:

$$F_t = A_t E_t \int_{\underline{a_t}}^{\infty} a_t \frac{g(a_t)}{1-G(\underline{a_t}))} da_t \tag{36}$$

where e_{it} and E_t are the mass of employment relationships at time t, at the firm and aggregate levels, respectively.

The wage bill is now also affected by idiosyncratic productivity.

$$W_t E_t = E_t \int_{\underline{a_t}}^{\infty} W(a_t) \frac{g(a_t)}{1-G(\underline{a_t}))} da_t \tag{37}$$

5.1.6 Shocks

Aggregate productivity is modeled as follows:

$$\ln A_{t+1} = \rho_A \ln A_t + \sigma_A \tag{38}$$

Idiosyncratic productivity shocks are drawn from an i.i.d log normal distribution g with CDF G:

$$a \sim LN(g) \tag{39}$$

5.1.7 Equilibrium

The endogenous variables to be solved are $C, V, \underline{a}, U$, and W. Knowing these the variables M, E, Q, P, and δ^n can be determined. The exogenous variables are τ and δ^x,the parameters of the aggregate productivity process A (ρ_A and σ_A), and the functional form and moments of the idiosyncratic productivity shocks distribution $g(a)$.

5.2 Methodology

The model is calibrated and then simulated.[15] The calibration of the parameters is summarized in Table 6.

Table 6

For all values, except those noted below, I follow the calibration values used in Section 4 above (see Table 3). For the additional parameters I use the following: for the CRRA utility parameter, I use the fairly standard coefficient $\omega = 2$; for the aggregate productivity shock I choose the parameters $\rho_A = 0.95$ and $\sigma_A = 0.0049$ so as to match the moments of U.S. GDP time series; in order to calibrate the two moments of the lognormal distribution assumed for idiosyncratic productivity, I normalize the mean to zero and choose the second moment so as to replicate the observed volatility of the job destruction rate. The standard deviation is therefore 0.12. Finally, for steady state values of the exogenous separation rate, total separation rate, and labor market outcomes (u, v, P, Q) I do the following: for the job finding rate, P, I use the value of Section 4 above. For the steady state unemployment rate u, I take into account the fact that the official rate may not be the relevant one. There are people out of the labor force that transit directly into employment and in terms of the model should be considered as unemployed. So while official unemployed averaged 6%, the wider measure can be high as 12%. Therefore I use the latter measure for the benchmark and as one variation I use 6%. There is also uncertainty with respect to the value of δ; I use 10% for the benchmark which is a relatively high estimate and 5% as a variation.

[15] I thank Michal Krause and Thomas Lubik for generously sharing with me their calibration-simulation MATLAB code.

The values of v and Q are then determined using the Beveridge curve relation and the definition of the matching function.

5.3 Results

Table 7 reports the results of the simulation of the benchmark model using the two alternatives of linear ($\gamma = 0, \phi = 1$) and convex ($\gamma = 2, , \phi = 0.3$) hiring costs functions.

Table 7

The tables indicate the following key findings:

(i) The baseline model with linear vacancy costs (fixed marginal costs) performs badly: unemployment, vacancies, market tightness and real wages are not as volatile as in the data. The standard deviation of vacancies is 16% of the data figure, unemployment volatility is 63% of the data figure, and tightness volatility is 28% of actual volatility. Job creation and job destruction are excessively volatile relative to the data. Vacancies are not as persistent as the data indicate. Wages are too pro-cyclical relative to the data. The co-movement of unemployment and vacancies is positively signed while in the data it is highly negative and endogenous job creation and destruction are also positively correlated, counter-factually. The model is able to capture the properties of output, mostly because of the formulation of the driving technology shock.

(ii) Moving to the richer formulation of hiring costs, which are (i) convex; (ii) a function of vacancy and hiring rates; and (iii) a function of average productivity, the results are mixed: in general the series become much more volatile. The model comes closer to the data in terms of real wages and market tightness. For example, the standard deviation of market tightness is 77% of actual volatility, compared to 28% in the linear case. But now the model moves much further away from the data on output and on job creation and destruction. Persistence statistics are slightly worse, with the counter-factual decline in the persistence of wages and vacancies. There is one notable improvement – the co-movement between unemployment and vacancies turns negative; note that many studies indicated that the positive co-movement typically obtained is a key problem with model predictions.

(iii) How sensitive are these results to the calibration of parameter values and to the steady state? Does the model fit improve under alternative values? Table 8 reports variations of parameter and steady state values for the richer hiring costs formulation. I try different values for the variance of the productivity distribution (different values of σ_{LN} from 0.05 to 0.14), a higher persistence parameter for aggregate productivity ($\rho_A = 0.99$), very low and very high values for the worker bargaining parameter ($\eta = 0.05, 0.95$), and two alternative steady state configurations (reported in the table and discussed above).

Table 8

First, results are very sensitive to the calibration of the shocks (persistence and volatility of the aggregate shock and variance of the idiosyncratic shock), of the bargaining parameter, and of the steady state rates of unemployment, separation, and vacancy matching. For example, output volatility varies wildly across calibration values. As the calibration of key parameters is not grounded in strong micro-based studies, uncertainty about true parameter values is meaningful here.

Second, in some of the alternative cases the model moments approach the data moments relative to the benchmark calibration. Does the model fit improve?

– The model gets closer to the data with low values of σ_{LN} w.r.t. the volatility of output and market tightness and w.r.t. the negative correlation between job creation and job destruction; with high values of σ_{LN} it gets closer to the data w.r.t. the persistence of wages and vacancies and w.r.t. the negative correlation between unemployment and vacancies; with intermediate values of σ_{LN} it is closer to the data w.r.t. the volatility of vacancies. But there is no single value that would bring the model consistently closer to fit the data.

– Real wages and vacancies become more persistent with higher persistence of the aggregate productivity shock or with very high or very low values of worker bargaining power.

– The negative co-movement between unemployment and vacancies is better captured with higher persistence of the aggregate productivity shock and with very low values of worker bargaining power.

5.4 Discussion

The emerging picture is the following: the model with fixed marginal vacancy costs is for the most part not sufficiently volatile, gets the co-movement of the key variables wrong, and misses to some extent the persistence statistics. The model with the richer formulation of hiring costs (convex and depending on vacancy and hiring rates and on average output) typically generates more volatile outcomes, in some cases excessively so; fits the u-v correlation much better; and fits the persistence statistics slightly less well. Moments, and hence model performance, are sensitive to calibrated parameter values, often highly so.

It is interesting to note that the partial equilibrium model, with data-based shocks, performs better than the general equilibrium model. The implication, then, is that the latter model needs to be modified in an attempt to generate a better fit with the data. There are many ways in which this can be attempted. One relates to the formulation of the driving shocks. In particular, the calibration of the log normal idiosyncratic productivity distribution is essential and needs to be based on more solid empirical knowledge (one issue is persistence of these shocks) . Likewise, different calibration of other parameters may yield a better fit; here, too, econometric micro studies may be needed. Another way is to modify the set up of the model. Possibilities include adding capital and capital adjustment costs, interacting with hiring costs (Merz and Yashiv (2007) point to the importance of this aspect of modelling); adding leisure-work choice to the households problem; and allowing for worker search on the job. A third avenue of exploration is to modify the model more substantially, in particular by changing its wage setting mechanism.

6 Conclusions

The paper began with the statement that the characterizations of U.S. labor market dynamics and their implications for the study of business cycles are topics of debate. It has examined three main issues.

On the data facts issue, the following are the key findings: key moments of the flows between the employment and unemployment pools were found to be similar across studies; a set of clear business cycle facts emerges, including countercyclical and volatile hiring and separation rates, pro-cyclical job finding rates, with considerable volatility of both accessions and separations. However, on the computation of flows between the out of the labor force and employment pools there is no agreement. The different computations – probably due to differential adjustments of the raw data – affect the implied series of job finding and separation rates.

On the business cycle implications, it turns out that both job finding and separation are key to the understanding of the cycle.

On the fit of the search and matching model, there is a mixed answer. On the one hand, the PE model captures the persistence, volatility, and some of the co-movement in the data. It was shown that a rich formulation of hiring costs and the appropriate stochastic process for separation shocks are needed for the fit. On the other hand, wage behavior is not captured in both PE and GE versions of the model and the latter does not perform well on other dimensions too. It can be concluded that much work still needs to be done on the issues examined by this paper; specific questions and directions for such work were proposed.

Data for Section 4: Sources and Definitions

All data are quarterly U.S. data for the period 1970:I - 2003:IV, except for hires and separations which begin in 1976:I and end in 2003:III.

variable	**symbol**	**Source**
Unemployment	U	CPS, BLS series id: LNS13000000
Employment (total), household survey	E	CPS, BLS series id: LNS12000000
Vacancies – Index of Help Wanted ads	V	Conference Board
Hires	QV	CPS, Boston Fed computations
Separations	δE	CPS, Boston Fed computations
Working age population	POP	CPS, BLS series id: LNU00000000
Labor share	$s = \frac{WE}{F}$	Table 1.12. NIPA, BEA
Productivity	$\frac{F}{E}$	BLS
Cost of finance (equity and debt)	r	Tables 1.1.5; 1.1.6 NIPA, BEA

Notes:

1. BLS series are taken from http://www.bls.gov/cps/home.htm

2. Vacancy data were downloaded from Federal Reserve Bank of St. Louis http://research.stlouisfed.org/fr

3. Hires were taken from Bleakley et al (1999) (see the latter for the construction methodology). I thank Jeffrey Fuhrer and Elizabeth Walat for their work on this series.

4. Working age population is total civilian noninstitutional population 16 years and older.

5. Total compensation of employees divided by GDP (taken from http://www.bea.doc.gov/bea/dn/home/

6. The cost of finance is a weighted average of the return on equity and debt.

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Table 1

Moments of Gross Worker Flows

a. Hiring Flows to Employment

study	sample	$\frac{M^{UE}}{E}$		$p^{UE} = \frac{M^{UE}}{U}$		$\frac{M^{NE}}{E}$		$\frac{M^{UE+NE}}{E}$	
		mean	**std.**	**mean**	**std.**	**mean**	**std.**	**mean**	**std.**
BD	1968:1-1986:5	0.017	0.002	0.257	0.053	0.015	0.002	0.033	0.002
R	1967:6-1993:5	0.017	0.002	0.263	0.046	0.029	0.004	0.046	0.003
BFF	1976:2-2003:12	0.016	0.002	0.247	0.030	0.013	0.001	0.030	0.003
FF	1994:1-2004:12	0.015	0.001	0.288	0.029	0.025	0.002	0.040	0.002
S	1967:4-2004:12	0.020	0.003	0.321	0.050	–	–	–	–
J	2000:12-2005:06	–	–	–	–	–	–	0.032	0.002

b. Separation Flows from Employment

study	sample	δ^{EU}		δ^{EN}		δ^{EN+EU}	
		mean	**std.**	**mean**	**std.**	**mean**	**std.**
BD	1968:1-1986:5	0.014	0.003	0.017	0.002	0.031	0.002
R	1967:6-1993:5	0.015	0.003	0.032	0.004	0.047	0.003
BFF	1976:2-2003:12	0.013	0.002	0.015	0.001	0.029	0.003
FF	1994:1-2004:12	0.013	0.001	0.027	0.002	0.040	0.002
S	1967:4-2004:12	0.020	0.003	0.030	0.004	0.050	0.005
S II	1951:1-2004:12					0.035	0.005
J	2000:12-2005:06	–	–	–	–	0.031	0.001

Notes:

1. In first column BD stands for Blanchard and Diamond (1989,1990), R stands for Ritter (1993), BFF stands for Bleakley, Ferris and Fuhrer (1999), FF stands for Fallick and Fleischmann (2004), S stands for Shimer (2007), SII stands for another computation from that same reference, and J stands for JOLTS data.

2. All numbers are the relevant flows as adjusted by the authors and are divided by seasonally-adjusted employment.

3. All data are monthly except for Shimer (2007) data, which are quarterly averages of monthly data. The latter were computed by converting the computed transition rate f to the probability rate F using the relation $F_t \equiv 1 - e^{-f_t}$

Table 2

Business Cycle Properties

a. Full Analysis

BFF (1999)	1st diff.		HP (1600)		HP (10^5)		BK	
$1976:I-2003:IV$	ρ	$\frac{\sigma_\cdot}{\sigma_y}$	ρ	$\frac{\sigma_\cdot}{\sigma_y}$	ρ	$\frac{\sigma_\cdot}{\sigma_y}$	ρ	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{M^{UE}}{E}, y$	-0.23	6.9	-0.68	3.9	-0.82	3.7	-0.84	3.4
$\frac{M^{NE}}{E}, y$	0.06	7.1	0.31	2.8	0.44	2.2	0.54	2.0
$\frac{M^{UE}+M^{NE}}{E}, y$	-0.12	5.9	-0.43	2.5	-0.59	2.1	-0.66	1.7
p^{UE}, y	0.31	7.3	0.76	4.5	0.83	4.8	0.89	4.1
δ^{EU}, y	-0.41	8.4	-0.77	4.9	-0.84	4.7	-0.88	4.4
δ^{EN}, y	-0.01	6.3	0.35	2.5	0.40	1.9	0.65	1.8
δ^{EU+EN}, y	-0.28	6.1	-0.53	2.6	-0.66	2.3	-0.71	1.8

b. Abridged Analysis (HP filter 1600)

	BD (1989,1990)		**R (1993)**		**FF (2004)**		**S (2007)**	
	ρ	$\frac{\sigma_\cdot}{\sigma_y}$	ρ	$\frac{\sigma_\cdot}{\sigma_y}$	ρ	$\frac{\sigma_\cdot}{\sigma_y}$	ρ	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{M^{UE}}{E}, y$	-0.75	4.4	-0.70	4.3	-0.45	4.6	-0.72	3.9
$\frac{M^{NE}}{E}, y$	0.56	4.9	0.33	2.2	0.26	5.2	–	–
$\frac{M^{UE}+M^{NE}}{E}, y$	-0.20	2.6	-0.37	1.9	0.01	3.5	–	–
p^{UE}, y	0.80	3.7	0.75	4.4	0.83	6.0	0.75	5.1
p^{UE+NE}, y	–	–	–	–	–	–	0.20	2.2
JF, y	–	–	–	–	–	–	0.83	4.9
δ^{EU}, y	-0.81	7.2	-0.80	5.7	-0.48	6.3	-0.70	4.7
δ^{EN}, y	0.54	4.6	0.41	1.9	0.33	4.6	0.38	2.4
δ^{EU+EN}, y	-0.41	3.0	-0.50	1.8	0.02	3.6	-0.35	2.2
sample	$1968:I-1986:II$		$1967:II-1993:II$		$1994:I-2004:IV$		$1967:II-2004:IV$	

Notes:

a. y is real GDP. Other abbreviations are explained in footnote 1 to Table 1.

b. All variables are logged; then they are either first differenced or are filtered using the Hodrick-Prescott filter (with smoothing parameter 1600 or 10^5) or with the Baxter King filter. Panel b reports only results with the Hodrick-Prescott filter, using smoothing parameter 1600.

c. ρ is the correlation; $\frac{\sigma_\cdot}{\sigma_y}$ is the relative standard deviation, where the standard deviation of filtered GDP is in the denominator.

d. For the Shimer (2007) data the following computations were used: (i) Define λ_t^{XY} as the Poisson arrival rate of a shock that moves a worker from state $X \in \{U, E, N\}$ to another state during period t. $\Lambda^{XY} = 1 - e^{\lambda_t^{XY}}$ is the associated full-period transition probability. The series λ_t^{NE} and λ_t^{UE} are available from Shimer's website (see http://home.uchicago.edu/~shimer/data/flows/). (ii) b. To obtain $\mathbf{p}^{UE+NE}$, the following formula was used:$\mathbf{p}^{UE+NE} = (1 - e^{\lambda_t^{UE}}) * \frac{CPS_U}{CPS_U + CPS_N} + (1 - e^{\lambda_t^{NE}}) * \frac{CPS_N}{CPS_U + CPS_N}$where CPS_U is quarterly average of monthly SA CPS data on the number of unemployed; CPS_N is quarterly average of monthly SA CPS data on the number of persons 'not in the labor force.' (iii) c. For Shimer II the JF probability was calculated from the job finding rate f_t, given in the above web page using $F_t = 1 - e^{-f_t}$. In Shimer (2007) F is given by: $F_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t}$where u_{t+1} = number of unemployed in period $t+1, u_t$ = number of unemployed in period t and u_{t+1}^s = short term unemployed workers, who are unemployed at date $t+1$ but held a job at some point during period t. An explanation of how short term unemployment was calculated is to be found in Shimer's (2007), Appendix A.

Table 3

PE Model: Calibration Values

a. Parameters, Exogenous Variables, and Steady State Values

Quarterly

Parameter/Variable	**symbol**	**value**
Matching	σ	0.4
Hiring (convexity)	γ	2
Hiring (vacancy weight)	ϕ	0.3
productivity growth	$\frac{A_{t+1}}{A_t}$	0.003536
discount factor	β	0.9929
separation rate	δ	0.0854
Unemployment	u	0.104
Labor share	$s = \frac{W}{F/E}$	0.58
Vacancy matching rate	Q	0.9

b. Implied Values

Matching scale parameter	μ	0.85
Hiring scale parameter	Θ	82
Wage bargaining parameter	ξ	0.41
Vacancy rate	v	0.089
Market tightness	$\frac{v}{u}$	0.86
Workers' hazard	P	0.77

Note:

The implied values of v, μ, Θ and ξ are solved for using the steady state relationships.

Table 4

PE Model and Data Moments

a. Persistence

$\rho(\widehat{u}_t, \widehat{u}_{t-1})$	Data	0.97
	Model	0.98
$\rho(\widehat{m}_t, \widehat{m}_{t-1})$	Data	0.85
	Model	0.99
$\rho(\widehat{s}_t, \widehat{s}_{t-1})$	Data	0.88
	Model	0.98

b. Volatility

$std(\widehat{e}_t)$	Data	0.022
	Model	0.021
$std(\widehat{u}_t)$	Data	0.188
	Model	0.182
$std(\widehat{m}_t)$	Data	0.085
	Model	0.051
$std(\widehat{s}_t)$	Data	0.016
	Model	0.056

c. Co-movement

$\rho(\widehat{u}_t, \widehat{m}_t)$	Data	0.81
	Model	0.997
$\rho(\widehat{u}_t, \widehat{P}_t)$	Data	-0.933
	Model	-1.00
$\rho(\widehat{n}_t, \widehat{s}_t)$	Data	-0.16
	Model	0.997
$\rho(\widehat{m}_t, \widehat{s}_t)$	Data	0.45
	Model	-0.99

Note:

All data are quarterly for the period 1970:I - 2003:IV, except for hires and separations which begin in 1976:I and end in 2003:III. Data sources and definitions are elaborated in the appendix.

Table 5

Counterfactuals

a. Convexity of Hiring Costs

	Data	**benchmark**	**counter-factual**
hiring costs		convex $\gamma = 2$	linear $\gamma = 0$
$\rho(\widehat{u}_t, \widehat{u}_{t-1})$	0.971	0.983	0.881
$\rho(\widehat{m}_t, \widehat{m}_{t-1})$	0.853	0.986	0.467
$\rho(\widehat{s}_t, \widehat{s}_{t-1})$	0.884	0.976	0.592
$std(\widehat{e}_t)$	0.022	0.021	0.015
$std(\widehat{u}_t)$	0.188	0.183	0.126
$std(\widehat{m}_t)$	0.085	0.052	0.090
$std(\widehat{\frac{v_t}{u_t}})$	–	0.219	0.103
$std(\widehat{s}_t)$	0.016	0.056	0.068
$\rho(\widehat{u}_t, \widehat{m}_t)$	0.810	0.997	0.888
$\rho(\widehat{u}_t, \widehat{P}_t)$	-0.933	-1.00	-0.743
$\rho(\widehat{n}_t, \widehat{s}_t)$	-0.160	0.997	0.936
$\rho(\widehat{m}_t, \widehat{s}_t)$	0.451	-0.989	-0.993
$\rho(\widehat{m}_t, \widehat{\delta}_t)$	0.908	0.862	0.599
$\rho(\widehat{u}_t, \widehat{v}_t)$	–	-0.985	0.580

b. The Separation Rate and the Interest Rate

	Data	benchmark	counterfactual 1	counterfactual 2	counterfactual 3
			δ AR=0.1	$\sigma_\delta = 0$	$\sigma_\beta = 0$
$\rho(\widehat{u}_t, \widehat{u}_{t-1})$	0.971	0.983	0.763	0.704	0.983
$\rho(\widehat{m}_t, \widehat{m}_{t-1})$	0.853	0.986	0.696	-0.152	0.986
$\rho(\widehat{s}_t, \widehat{s}_{t-1})$	0.884	0.976	0.553	0.262	0.977
$std(\widehat{e}_t)$	0.022	0.021	0.001	0.00006	0.021
$std(\widehat{u}_t)$	0.188	0.183	0.004	0.0006	0.183
$std(\widehat{m}_t)$	0.085	0.052	0.001	0.0005	0.051
$std(\frac{\widehat{v_t}}{u_t})$	–	0.219	0.006	0.001	0.219
$std(\widehat{s}_t)$	0.016	0.056	0.002	0.0006	0.056
$\rho(\widehat{u}_t, \widehat{m}_t)$	0.810	0.997	0.886	0.279	0.997
$\rho(\widehat{u}_t, \widehat{P}_t)$	-0.933	-1.00	-0.984	-0.620	-1.00
$\rho(\widehat{n}_t, \widehat{s}_t)$	-0.160	0.997	0.917	0.304	0.997
$\rho(\widehat{m}_t, \widehat{s}_t)$	0.451	-0.989	-0.627	0.830	-0.989
$\rho(\widehat{m}_t, \widehat{\delta}_t)$	0.908	0.862	0.304	–	0.862
$\rho(\widehat{u}_t, \widehat{v}_t)$	–	-0.985	-0.733	-0.140	-0.985

c. Convexity and the Separation Rate

	Data	benchmark	counter-factual
			$\gamma = 0; \sigma_\delta = \sigma_\beta = 0$
$\rho(\widehat{u}_t, \widehat{u}_{t-1})$	0.971	0.983	-0.118
$\rho(\widehat{m}_t, \widehat{m}_{t-1})$	0.853	0.986	-0.556
$\rho(\widehat{s}_t, \widehat{s}_{t-1})$	0.884	0.976	-0.556
$std(\widehat{e}_t)$	0.022	0.021	0.00004
$std(\widehat{u}_t)$	0.188	0.183	0.00004
$std(\widehat{m}_t)$	0.085	0.052	0.0007
$std(\widehat{\frac{v_t}{u_t}})$	–	0.219	0.0008
$std(\widehat{s}_t)$	0.016	0.056	0.0004
$\rho(\widehat{u}_t, \widehat{m}_t)$	0.810	0.997	0.720
$\rho(\widehat{u}_t, \widehat{P}_t)$	-0.933	-1.00	0.255
$\rho(\widehat{n}_t, \widehat{s}_t)$	-0.160	0.997	0.773
$\rho(\widehat{m}_t, \widehat{s}_t)$	0.451	-0.989	-0.997
$\rho(\widehat{m}_t, \widehat{\delta}_t)$	0.908	0.862	-
$\rho(\widehat{u}_t, \widehat{v}_t)$	–	0.985	0.588

Note:

All data are quarterly for the period 1970:I - 2003:IV, except for hires and separations which begin in 1976:I and end in 2003:III.

Table 6

GE Model: Calibration Values

Quarterly

a. Parameters, Exogenous Shocks and Steady State Values

Parameter/Variable	**symbol**	**value**
Utility, CRRA	ω	2
Discounting	β	0.99
Worker bargaining	ξ	0.5
Matching	σ	0.4
Hiring (convexity)	γ	2
Hiring (vacancy weight)	ϕ	0.3
Unemployment rate	u	0.12
Job finding rate	P	0.80
Exogenous separation rate	δ^x	0.068
Separation rate	δ	0.10
Persistence of aggregate shock	ρ_A	0.90
Std of aggregate shock	σ_A	0.0049
Mean of idiosyncratic shock	μ_{LN}	0
Std. of idiosyncratic shock	σ_{LN}	0.12

b. Implied Values

Parameter/Variable	**symbol**	**value**
Matching scale parameter	μ	0.74
Hiring scale parameter	Θ	4.72
Vacancy rate	v	0.14
Market tightness	$\frac{v}{u}$	1.16
Matching rate	Q	0.7

Table 7

GE Model and Data Moments:

Benchmark

Relative standard deviations (reative to output)

	U.S. data	**linear vacancy costs**	**convex vacancy costs**
Output (own s.d)	1.62	1.65	7.78
Real Wages	0.69	0.30	0.42
Unemployment	6.90	4.33	10.63
Vacancies	8.27	1.32	1.23
Market Tightness	14.96	4.19	11.58
JCR	2.55	7.75	14.62
JDR	3.73	7.88	14.77

Autocorrelation

	U.S. data	**linear vacancy costs**	**convex vacancy costs**
Output	0.87	0.98	0.99
Real Wage	0.91	0.85	0.69
Unemployment	0.91	0.91	0.98
Vacancies	0.92	0.60	0.43
Market Tightness	0.92	0.98	0.99

Correlations

	U.S. data	**linear vacancy costs**	**convex vacancy costs**
$\rho(w, Y)$	0.57	0.86	0.88
$\rho(u, v)$	-0.95	0.27	-0.72
$\rho(JDR, JCR)$	-0.36	0.51	0.91

Notes:

1. Linear costs use $\gamma = 0, \phi = 1$.Convex costs use $\gamma = 2, \phi = 0.3$.

Table 8

GE Model and Data Moments:

Variations

a. Absolute standard deviations

	U.S. data	**benchmark**
Output	1.62	7.89
Real Wage	1.12	3.27
Unemployment	11. 18	83.87
Vacancies	13. 40	9.6
Tightness	24. 24	91.29
JCR	4. 13	115.3
JDR	6. 04	116.6

	U.S. data	$\sigma_{LN} = 0.05$	$\sigma_{LN} = 0.07$	$\sigma_{LN} = 0.09$	$\sigma_{LN} = 0.14$
Output	1.62	3.73	4.55	5.52	13.20
Real Wage	1.12	3.55	2.71	2.61	5.26
Unemployment	11. 18	42.0	46.22	56.29	145.6
Vacancies	13. 40	26.44	14.54	10.32	14.13
Tightness	24. 24	37.61	47.85	60.44	158.9
JCR	4. 13	106.7	79.99	82.93	197.8
JDR	6. 04	100.3	78.46	83.18	198.6

	U.S. data	$\rho_A = 0.99$	$\sigma_A = 0.01$
Output	1.62	43.17	16.45
Real Wage	1.12	16.09	6.77
Unemployment	11. 18	466.6	174.8
Vacancies	13. 40	43.49	19.91
Tightness	24. 24	510	190.4
JCR	4. 13	630.8	239.7
JDR	6. 04	632.5	242.6

	U.S. data	$\eta = 0.05$	$\eta = 0.95$
Output	1.62	3.16	6.47
Real Wage	1.12	0.23	6.24
Unemployment	11. 18	23.88	90.5
Vacancies	13. 40	9.92	28.94
Tightness	24. 24	33.80	62.13
JCR	4. 13	19.30	184.8
JDR	6. 04	21.23	185.6

	U.S. data	$\rho_x = 0.077$ $q = 0.7$ $p = 0.8$ $u = 0.12$	$\rho_x = 0.035$ $q = 0.98$ $p = 0.8$ $u = 0.06$
Output	1.62	5.57	9.56
Real Wage	1.12	2.90	3.89
Unemployment	11. 18	61.71	228.3
Vacancies	13. 40	7.66	6.80
Tightness	24. 24	64.45	229.9
JCR	4. 13	96.44	332.3
JDR	6. 04	96.74	335.3

b. Autocorrelation

	U.S. data	**benchmark**
Output	0.87	0.99
Real Wage	0.91	0.69
Unemployment	0.91	0.98
Vacancies	0.92	0.43
Market Tightness	0.92	0.99

	U.S. data	$\boldsymbol{\sigma}_{LN} = 0.05$	$\boldsymbol{\sigma}_{LN} = 0.07$	$\boldsymbol{\sigma}_{LN} = 0.09$	$\boldsymbol{\sigma}_{LN} = 0.14$
Output	0.87	0.98	0.986	0.99	0.99
Real Wage	0.91	-0.53	-0.12	0.32	0.89
Unemployment	0.91	0.50	0.87	0.96	0.97
Vacancies	0.92	-0.74	-0.53	-0.16	0.81
Tightness	0.92	0.95	0.985	0.99	0.99

	U.S. data	$\boldsymbol{\rho}_A = 0.99$	$\boldsymbol{\sigma}_A = 0.01$
Output	0.87	0.99	0.99
Real Wage	0.91	0.99	0.71
Unemployment	0.91	0.99	0.98
Vacancies	0.92	0.98	0.47
Tightness	0.92	0.99	0.99

	U.S. data	$\boldsymbol{\eta = 0.05}$	$\boldsymbol{\eta = 0.95}$
Output	0.87	0.99	0.99
Real Wage	0.91	0.99	0.90
Unemployment	0.91	0.99	0.99
Vacancies	0.92	0.99	0.95
Tightness	0.92	0.99	0.99

	U.S. data	$\rho_x = 0.077$ $q = 0.7$ $p = 0.8$ $u = 0.12$	$\rho_x = 0.035$ $q = 0.98$ $p = 0.8$ $u = 0.06$
Output	0.87	0.99	0.99
Real Wage	0.91	0.42	0.76
Unemployment	0.91	0.97	0.99
Vacancies	0.92	-0.23	-0.20
Tightness	0.92	0.99	0.99

c. Correlations

	U.S. data	**benchmark**
$\rho(w,Y)$	0.57	0.88
$\rho(u,v)$	-0.95	-0.72
$\rho(JDR,JCR)$	-0.36	0.91

	U.S. data	$\boldsymbol{\sigma}_{LN}=0.05$	$\boldsymbol{\sigma}_{LN}=0.07$	$\boldsymbol{\sigma}_{LN}=0.09$	$\boldsymbol{\sigma}_{LN}=0.14$
$\rho(w,Y)$	0.57	0.30	0.56	0.74	0.96
$\rho(u,v)$	-0.95	0.48	0.01	-0.35	-0.91
$\rho(JDR,JCR)$	-0.36	-0.36	0.35	0.72	0.97

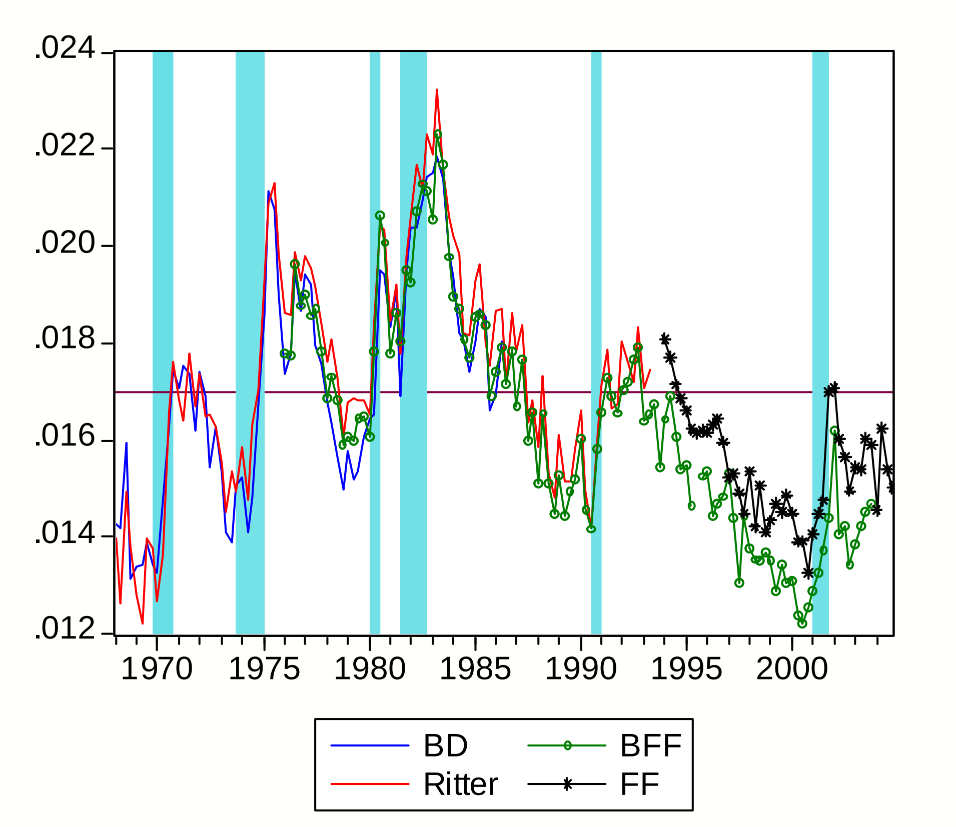
	U.S. data	$\boldsymbol{\rho}_A=0.99$	$\boldsymbol{\sigma}_A=0.01$
$\rho(w,Y)$	0.57	0.995	0.89
$\rho(u,v)$	-0.95	-0.996	-0.74
$\rho(JDR,JCR)$	-0.36	0.991	0.92

	U.S. data	$\boldsymbol{\eta}=\mathbf{0.05}$	$\boldsymbol{\eta}=\mathbf{0.95}$
$\rho(w,Y)$	0.57	0.998	0.95
$\rho(u,v)$	-0.95	-0.999	0.98
$\rho(JDR,JCR)$	-0.36	0.84	0.97

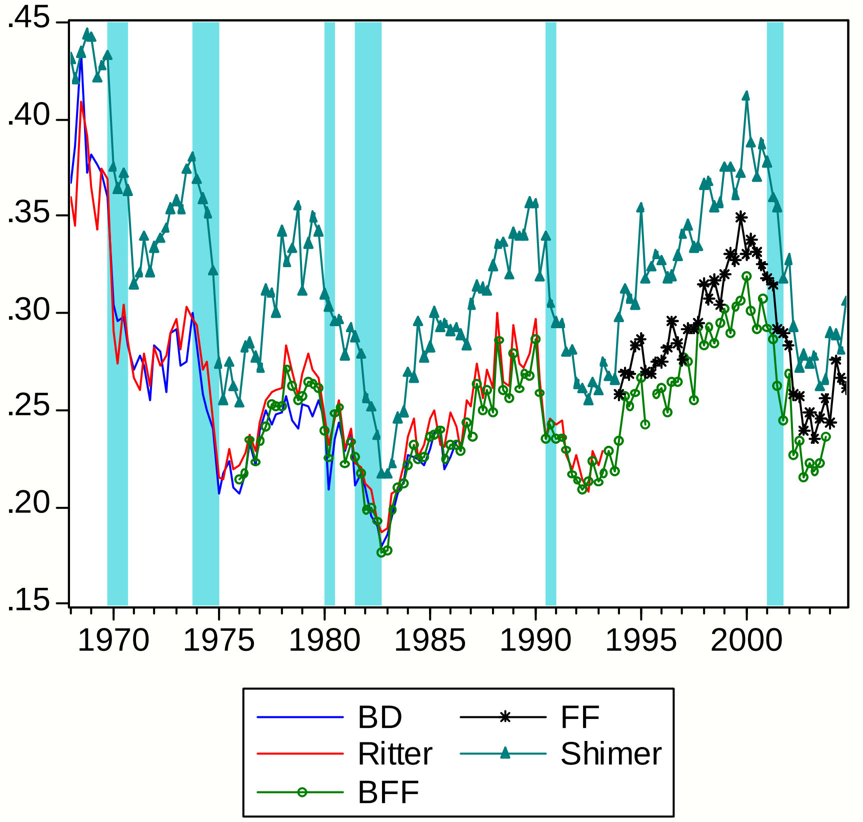
	U.S. data	$\rho_x=0.077$ $q=0.7$ $p=0.8$ $u=0.12$	$\rho_x=0.035$ $q=0.98$ $p=0.8$ $u=0.06$
$\rho(w,Y)$	0.57	0.776	0.91
$\rho(u,v)$	-0.95	-0.29	-0.22
$\rho(JDR,JCR)$	-0.36	0.81	0.97

Figure 1

Flows from Unemployment to Employment



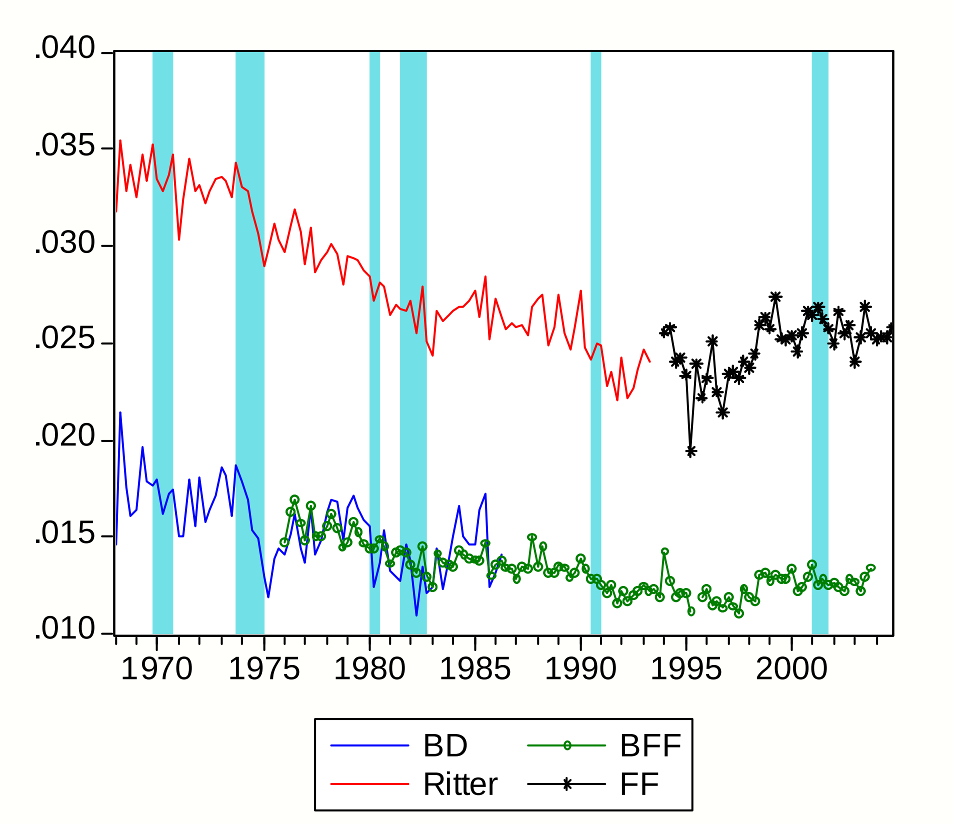
a. Hiring Rates $\frac{M^{UE}}{E}$



b. Job Finding Rates $\frac{M^{UE}}{U}$

Figure 2

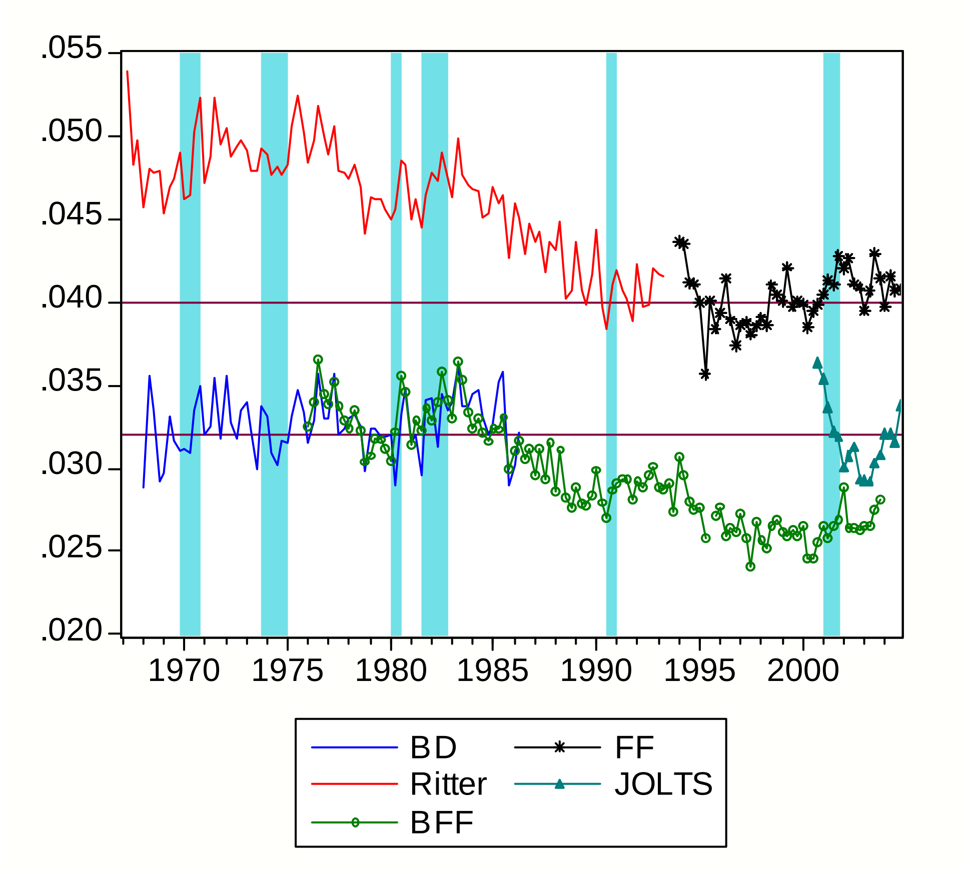
Flows from Out of the Labor Force to Employment



Matching Rates $\frac{M^{NE}}{E}$

Figure 3

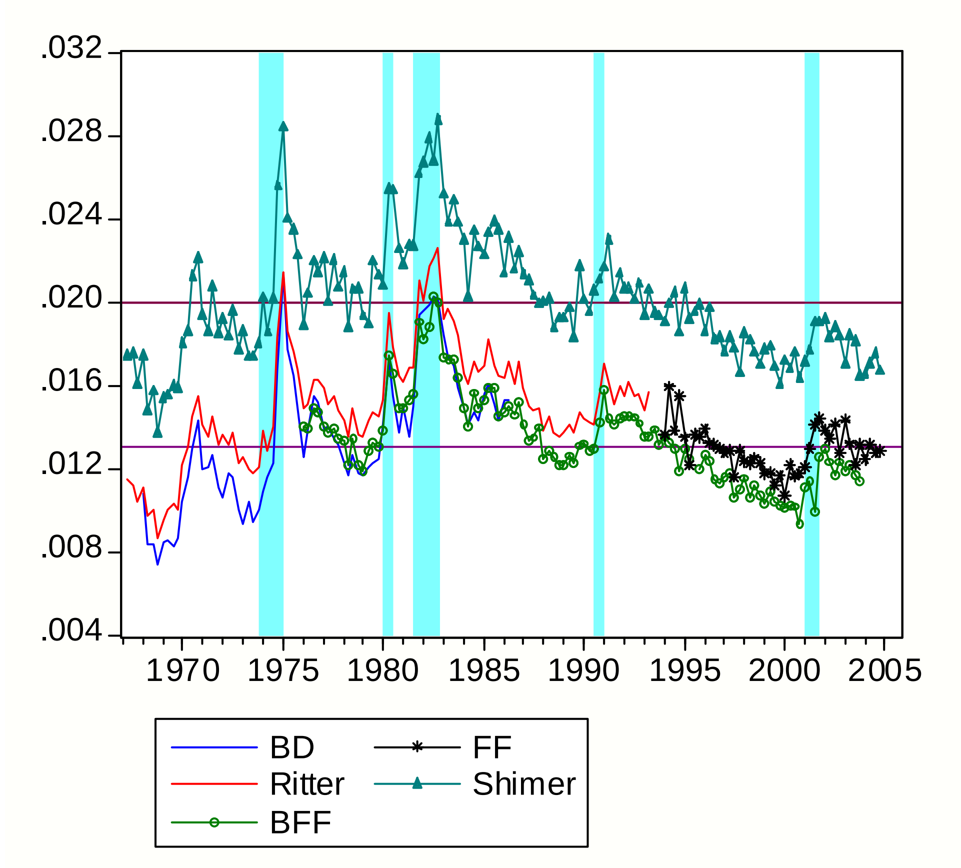
Total Hirings



Hiring Rates $\frac{M^{UE+NE}}{E}$

Figure 4

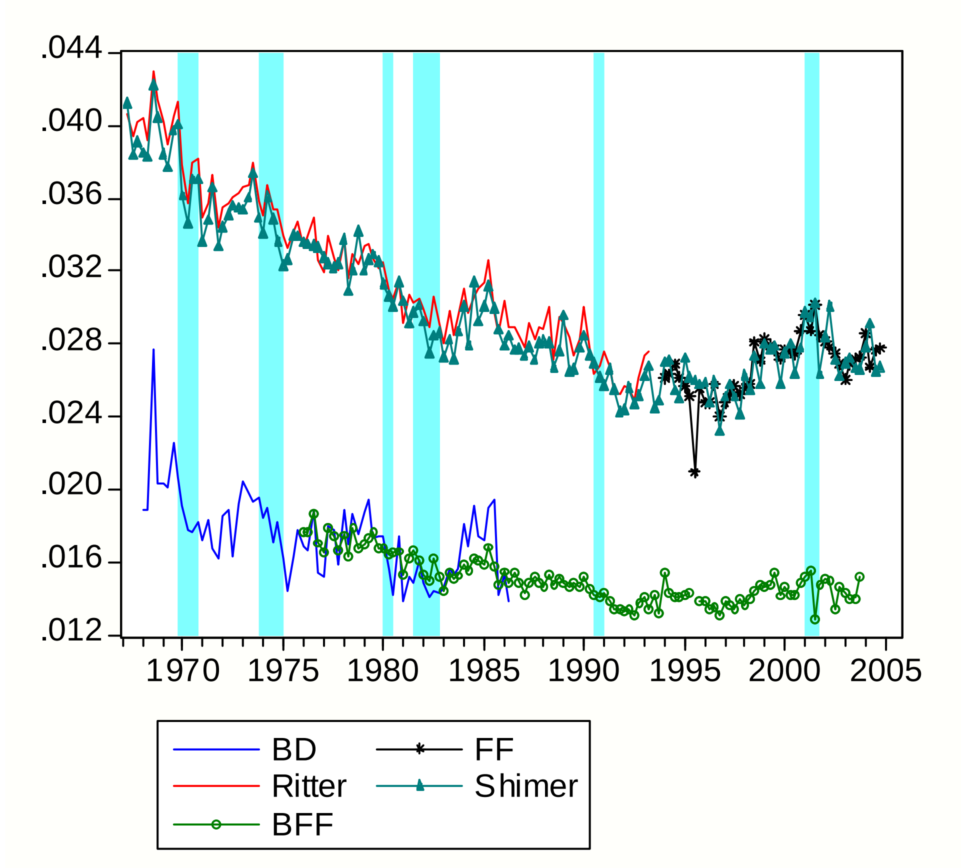
Flows from Employment to Unemployment



Separation rates δ^{EU}

Figure 5

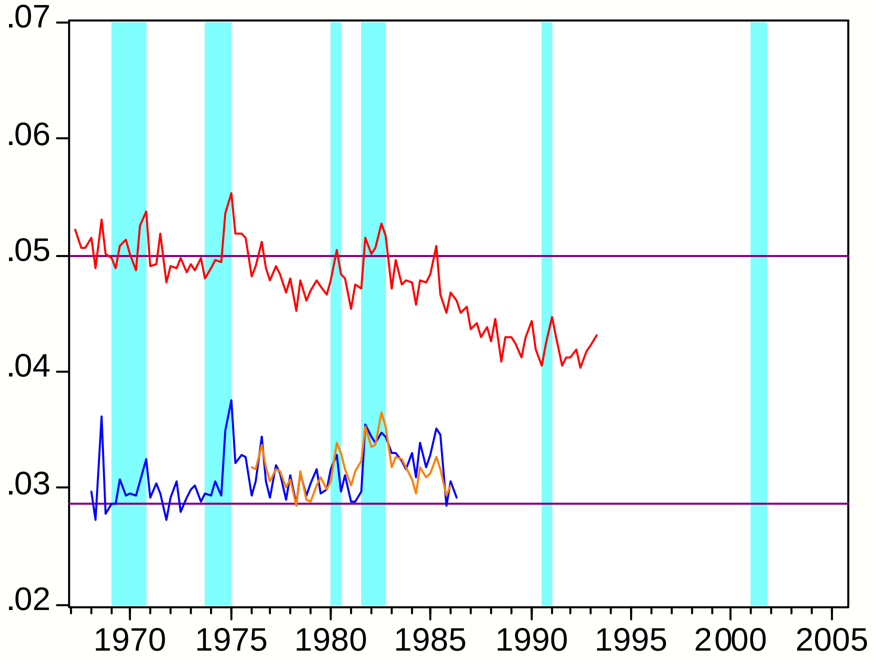
Flows from Employment to Out of the Labor Force



Separation Rates δ^{EN}

Figure 6

Total Separation Rates



Separation Rates δ^{EU+EN}

Figure 7

FOC for Vacancy Creation

Alternative Values of γ

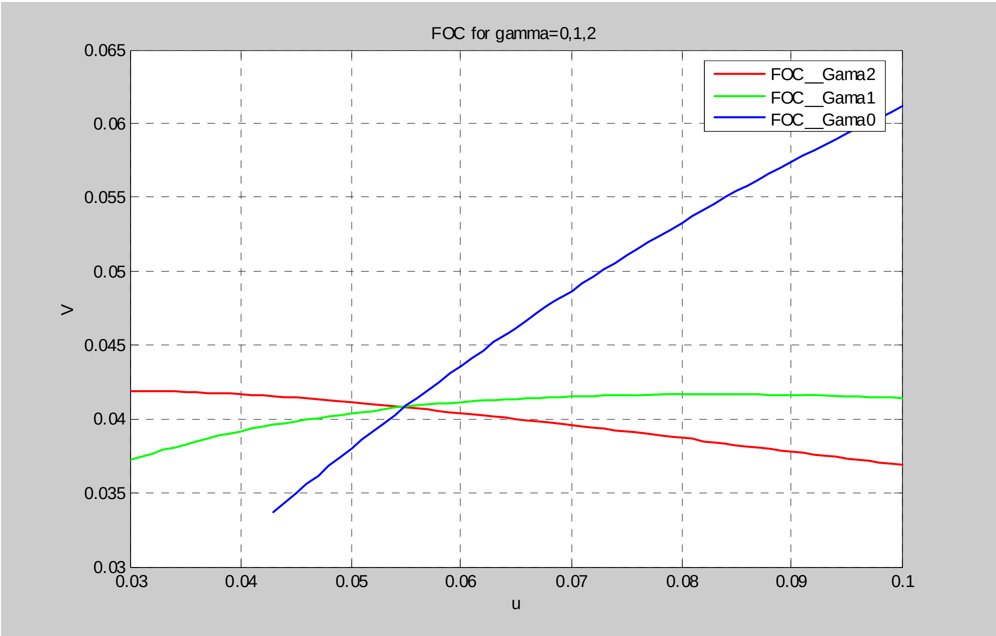
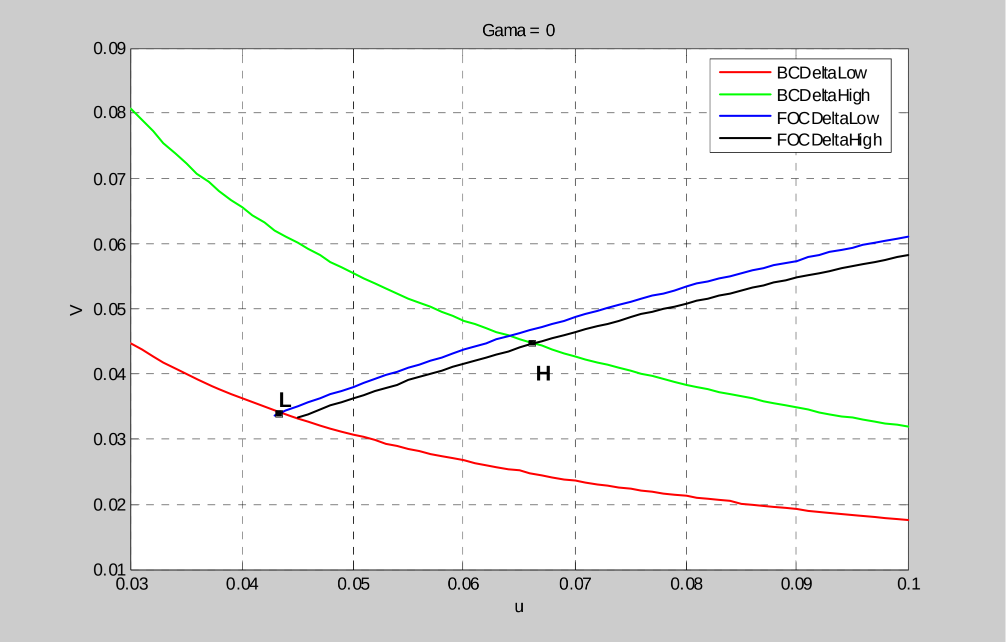
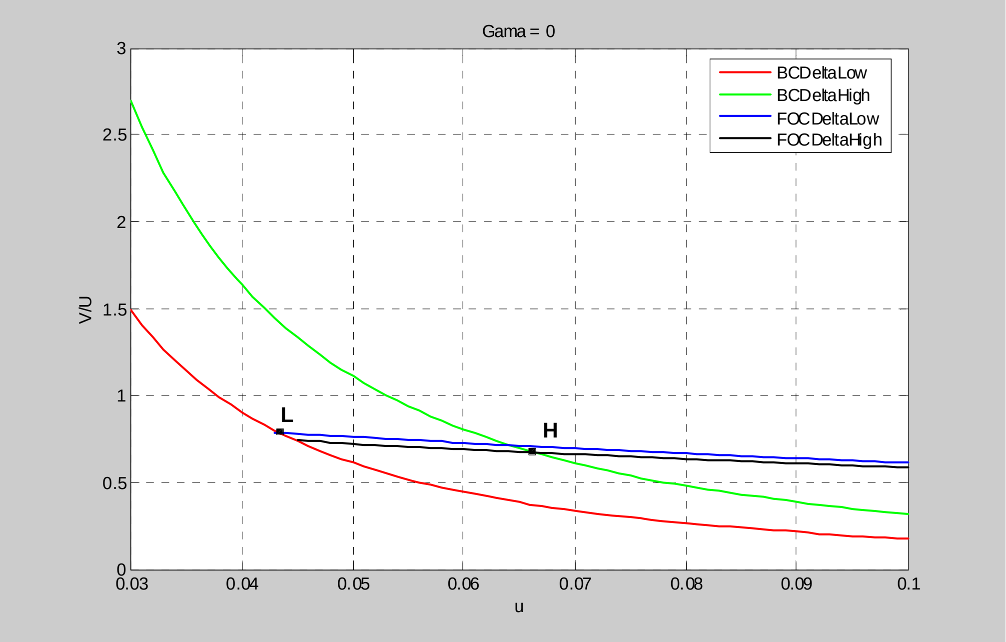


Figure 8

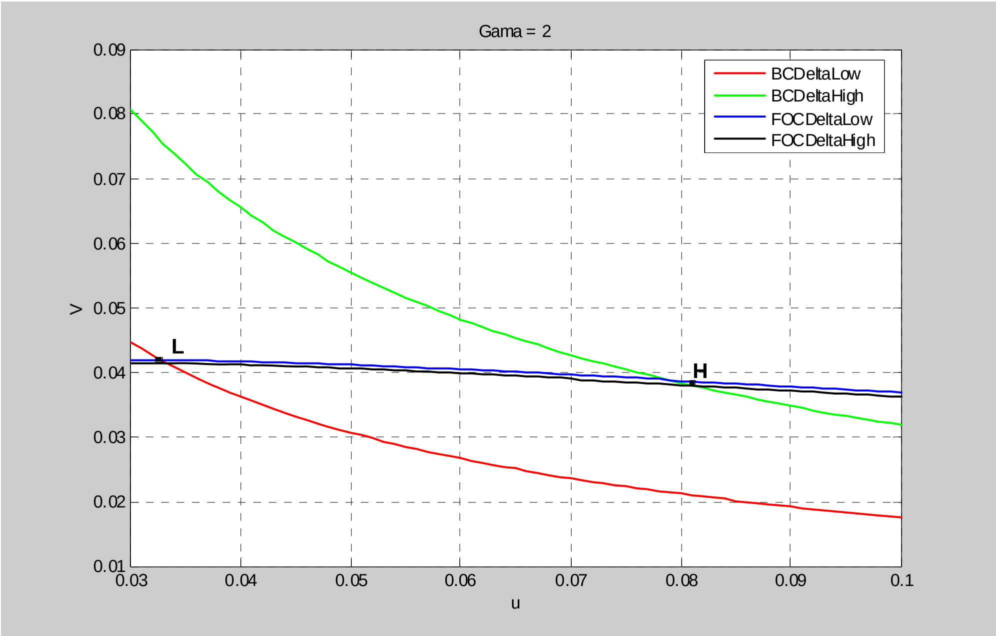
Increase in the Separation Rate δ

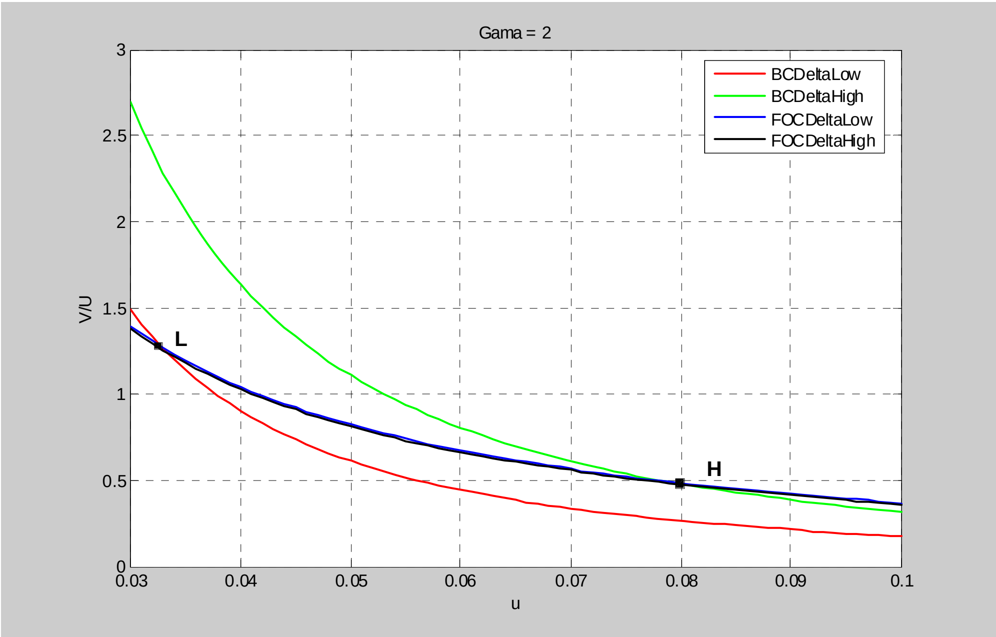
a. $\gamma = 0$




Gama = 0
BCDeltaLow
BCDeltaHigh
FOCDeltaLow
FOCDeltaHigh
L
H
V/U
u
3
2.5
2
1.5
1
0.5
0
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1

b. $\gamma = 2$


Gama = 2
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
V
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
u
BCDeltaLow
BCDeltaHigh
FOCDeltaLow
FOCDeltaHigh
L
H


Gama = 2
BCDeltaLow
BCDeltaHigh
FOCDeltaLow
FOCDeltaHigh
V/U
u
L
H
3
2.5
2
1.5
1
0.5
0
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1