Vacancy Posting, Job Separation and Unemployment Fluctuations*

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Abstract

This paper studies the relative importance of the two main determinants of cyclical unemployment fluctuations: vacancy posting and job separation. Using a matching function to model the flow of new jobs, I draw on Shimer's (2007) unemployment flow rates decomposition and find that job separation and vacancy posting respectively account for about 40 and 60 percent of unemployment's variance. I also generalize the flow rates decomposition to higher-order moments, and I find that job separation contributes to about 60 percent of unemployment steepness asymmetry, a stylized fact of the jobless rate. Finally, while vacancy posting is, on average, the most important contributor of unemployment fluctuations, the opposite is true around business cycle turning points, when job separation is responsible for most of unemployment movements.

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1 Introduction

At the beginning of a recession, does unemployment go up because of less hiring, more job loss or both? What is the most effective policy to mitigate that increase, a firing tax, a hiring subsidy or a combination of both? And why does unemployment increase faster than it goes down?

The answers to these questions will depend for a large part on the determinants of unemployment fluctuations. In this paper, I study the relative importance of the two main driving forces of cyclical unemployment: vacancy posting, i.e. firms' recruiting efforts, and job separation.[1]

An extensive literature has studied worker flows over the business cycle, and more recently Shimer (2007) focused on individual workers' transition rates –the job finding rate (JF) and the job separation rate (JS)– and concluded that unemployment inflows contribute much less to unemployment fluctuations than unemployment outflows.[2] This very influential conclusion led to a recent modeling trend that assumes that the job separation rate is acyclical.[3] However, this interpretation relies on the implicit assumption that JF and JS are two independent determinants of unemployment. While a standard Mortensen-Pissarides model (MP, 1994) predicts that JF and JS are indeed exogenous, this needs not be the case in the data.

Granger-causality tests show that JS Granger-causes JF, casting some doubt on the independence of JF and complicating the interpretation of a decomposition between the job finding rate and the job separation rate. If JF depends on JS, a flow rates decomposition may give a biased picture of the relative importance of hiring and job separation as driving forces of cyclical unemployment. In particular, the contribution of job separation is likely to be under-

[1] In this paper, as in much of the literature on unemployment fluctuations, I omit inactivity-unemployment flows, and focus only on employment-unemployment flows. See Shimer (2007) for evidence supporting this assumption.

[2] For work on gross worker flows, see Darby, Plant and Haltiwanger (1986), Blanchard and Diamond (1989, 1990), Bleakley et al (1999), Fallick and Fleischman (2004) and Fujita and Ramey (2006) among others. Shimer (2007), Elsby, Michaels and Solon (2009), Elsby, Hobijn, and Sahin (2008), Nekarda (2008) and Fujita and Ramey (Forthcoming) focus instead on transition rates between employment, unemployment and out of labor force.

[3] See, among others, Blanchard and Gali (2008), Gertler and Trigari (2009) and Hall (2005).

estimated. JF is the ratio of new hires to the stock of unemployed. As a result, an increase in JS with no change in hiring will increase unemployment and mechanically lower JF. In that case, a decomposition between JF and JS will attribute the higher unemployment to a low JF, i.e. little hiring, even though the true cause was an increase in job separation.

The first contribution of this paper is to propose an alternative decomposition –between vacancy posting and JS– that can better assess the relative importance of hiring and job separation. By using a measure of vacancy posting, I can model the flow of new jobs with a matching function and isolate the fluctuations in the job finding rate caused solely by changes in firms' recruiting efforts. I find that the contribution of the job separation rate to unemployment's variance is close to 40 percent instead of 25 percent using Shimer's (2007) methodology. Thus, not modeling the cyclicality of the job separation rate will lead researchers to understate the volatility of unemployment.

The second contribution of this paper is to extend the method pioneered by Shimer (2007), Elsby, Michaels and Solon (2009) and Fujita and Ramey (2009) and study the determinants of unemployment's higher-order moments. I find that JS plays an important role with respect to skewness and kurtosis. In particular, the steepness asymmetry of unemployment –the fact that increases are steeper than decreases– is due in large part to the job separation rate, which accounts for more than 60 percent of first-differenced unemployment skewness.[4] Further, JS and vacancy posting contribute in roughly equal proportions to unemployment's mild kurtosis. However, this decomposition hides an important difference between the two margins: vacancy posting presents a large negative excess kurtosis but JS presents a positive excess kurtosis. This result suggests that vacancy posting drives unemployment during normal times but that job separation is responsible for rare but violent fluctuations in unemployment.

To explore this idea further, I depart from an average decomposition and analyze the relative contributions of JS and vacancy posting at business cycles turning points. I find that

[4] A large literature has documented a non-trivial asymmetry in steepness for the cyclical component of unemployment; that increases in unemployment are steeper than decreases. See, among others, Neftci (1984), Delong and Summers (1986), Sichel (1993) and McKay and Reis (2008).

job separation is responsible for almost all of the movements in unemployment during the first two quarters after unemployment reaches a low or a high, and that vacancy posting does not become the main contributor until a year later. Thus, ignoring the cyclicality of the job separation margin will lead researchers to downplay the asymmetric behavior of unemployment and understate the breadth and speed of adjustment of unemployment around turning points.

The remainder of the paper is organized as follows: Section 2 reviews Shimer's (2007) method and highlights the dynamic interactions between JF and JS; Section 3 assesses the contributions of vacancy posting and JS to unemployment's second, third and fourth moments, Section 4 studies the behavior of the hazard rates at business cycles turning points; and Section 5 offers some concluding remarks.

2 The contributions of JF and JS

In this section, I briefly review Shimer's (2007) methodology to identify the contributions of JF and JS to unemployment's variance and discuss the possible endogeneity of the job finding rate.

2.1 The variance decomposition approach

Denoting $u_{t+\tau}$ the unemployment rate at instant $t+\tau \in \mathbb{R}_+$ with $t \in \mathbb{N}$ and $\tau \in [0,1[$, Shimer (2007) postulates that during a "period t" of one month – i.e. $\tau \in [0,1[$ – all unemployed workers find a job according to a Poisson process with *constant* arrival rate $\bar{f}_t$ and all employed workers lose their job according to a Poisson process with *constant* arrival rate $\bar{s}_t$. As a result, we have the first-order differential equation:

$$\frac{du_{t+\tau}}{d\tau} = \bar{s}_t \left(1 - u_{t+\tau}\right) - \bar{f}_t u_{t+\tau}. \tag{1}$$

By further assuming that the job finding rate is the same for all candidate workers, Shimer (2007) estimates the job finding rate separately by solving the first-order differential equation

$$\frac{du_{t+\tau}}{d\tau} - \frac{du^{<1}_{t+\tau}}{d\tau} = \bar{f}_t \left(u_{t+\tau} - u^{<1}_{t+\tau}\right)$$

where $u^{<1}_{t+\tau}$ denotes the stock of unemployed workers at date $t+\tau$ with duration less than one month. The estimated job finding rate over $[t, t+1[$ takes the form

$$\bar{f}_t = -\ln(1-\bar{F}_t) \text{ where } \bar{F}_t = 1 - \frac{u_{t+1} - u^{<1}_{t+1}}{u_t} \tag{2}$$

Note however that this result is only an approximation, as the job finding rate may not be constant over $[t, t+1[$. Equation (2) gives an estimate of the *average* job finding rate $\bar{f}_t$ over $[t, t+1[$ and is valid under the assumption that movements in $f_{t+\tau}$ (the job finding rate at time $t+\tau$) are small over the month so that $f_{t+\tau} \simeq \bar{f}_t$, $\forall \tau \in [0, 1[$.

The separation rate can then be estimated by solving (1) over $[t, t+1]$ and finding $\bar{s}_t$ such that the solution $u_{t+\tau}$ equals u_{t+1} for $\tau = 1$. Again, this estimation method relies on the assumptions that the job finding rate and the job separation rate are both constant over each time period and independent of unemployment.

Shimer (2007) then argues that the measured magnitudes of the two hazard rates ensure that at a quarterly frequency, it is reasonable to use the following approximation

$$u_t \simeq \frac{\bar{s}_t}{\bar{s}_t + \bar{f}_t} \equiv u^{ss}_t \tag{3}$$

Following Elsby, Michaels and Solon (2009) and Fujita and Ramey (2009), log-linearizing (3) gives

$$d\ln u^{ss}_t = (1 - u^{ss}_t)\left[d\ln \bar{s}_t - d\ln \bar{f}_t\right] + \epsilon_t \tag{4}$$

or

$$du^{ss}_t = du^{sr}_t + du^{jf}_t + \epsilon_t$$

so that the deviations of unemployment can be decomposed into a component depending on the job separation rate, a component depending on the job finding rate and a residual term. Fujita and Ramey (2009) assess the separate contributions of the separation and job finding rates by noting that

$$Var\left(du_t^{ss}\right) = Cov(du_t^{ss}, du_t^{jf}) + Cov(du_t^{ss}, du_t^{sr}) + Cov(du_t^{ss}, \epsilon_t). \quad (5)$$

so that $\beta^{jf} = \frac{Cov(du_t^{ss}, du_t^{jf})}{Var(du_t^{ss})}$ and $\beta^{sr} = \frac{Cov(du_t^{ss}, du_t^{sr})}{Var(du_t^{ss})}$ measure the contributions of the job separation rate and the job finding rate to unemployment's variance.

2.2 The dynamic interactions between JS and JF

To interpret (5), the job finding rate and the job separation rate must be two independent determinants of unemployment. In a standard MP model, this is indeed the case. The job finding rate is a function of the vacancy-unemployment ratio alone which, in turn, is solely a function of productivity, an exogenous variable. Similarly, the job separation rate is solely a function of productivity.

However, outside of the standard MP model, the exogeneity of JF and JS is not guaranteed, and a flow rates decomposition may be biased if JF and JS are not independent of each other. As Fujita and Ramey (2009) first emphasized, a variance decomposition may overstate or understate the true contributions of hiring and separation because the steady-state approximation suppresses the dynamic interaction between JS and JF. For example, if a high separation rate leads to a low job finding rate next period, one may attribute the high unemployment next period to the low job finding rate, even though the high separation rate was the true cause.

Empirically, a simple way to highlight the endogeneity between JF and JS is to run Granger-causality tests between the two series. Table 1 presents the results using specifications with one to three lags.[5] In all cases, I can strongly reject that JS does not Granger-cause JF. Granger-

[5] With Granger-causality tests, the results can be sensitive to the number of lags used in the regressions as well as the detrending method. I report the results with one to three lags, as the Akaike information criteria equally favors those three specifications. The results in Table 1 were obtained after including a quadratic trend

causality running from JF to JS is weaker, and with one lag, I can accept the null that JF does not Granger-cause JS. In a similar vein, Fujita and Ramey (2009) extend their variance decomposition by allowing for some dynamic interactions between JF and JS. They find that the contribution of the separation rate increases markedly, suggesting that some endogeneity running from the job separation rate to the job finding rate could bias the contribution of JS downwards.

3 The contributions of vacancy posting and job separation

The analysis in the previous section suggests that a steady-state variance decomposition exercise between JF and JS may be difficult to interpret because of the dynamic interactions between the two series. In this section, I first argue that a decomposition between vacancy posting and the job separation rate can mitigate this problem and better assess the relative importance of hiring and job separation. I then estimate a matching function to model the movements in the job finding rate with a measure of vacancy posting. Finally, I use the hazard rate decomposition approach to evaluate the contributions of vacancy posting and job separation to unemployment's variance, skewness and kurtosis.

3.1 Focusing on vacancy posting and JS

If JF depends on JS, the variance decomposition (5) may give a biased picture of the relative importance of hiring and job separation as driving forces of cyclical unemployment. By using a measure of vacancy posting, I can isolate the fluctuations in the job finding rate caused solely by changes in firms' recruiting efforts and better assess the contribution of the hiring margin.

The job finding rate is the ratio of new hires to the stock of unemployed, so that if h_t denotes the number of new hires at instant t, the job finding rate is given by $f_t = \frac{h_t}{u_t}$, where u_t is the number of unemployed. By modeling the number of hirings with a standard Cobb-Douglas matching function with constant returns to scale, I can write $h_t = h_0 u_t^{\sigma} v_t^{1-\sigma}$ with v_t

in the regressions. Removing the trend gives similar results.

the number of job openings.[6] The job finding rate then takes the form

$$f_t = h_0 \left(\frac{v_t}{u_t} \right)^{1-\sigma}$$

Keeping vacancies constant, an increase in the job separation rate will increase steady-state unemployment and mechanically lower the job finding rate. Since unemployment converges to its steady-state in less than a quarter (Shimer, 2007), a steady-state decomposition between JS and JF at a quarterly frequency may attribute the higher unemployment to a low JF, i.e. little hiring, even though the true cause was an increase in job separation.[7] In contrast, a decomposition between vacancy posing and JS avoids that problem by isolating the movements in JF caused only by changes in firms' recruiting efforts, not by fluctuations in unemployment.

An additional advantage of focusing on vacancy posting and the job separation rate is that these variables correspond to the control variables that economic agents adjust in response to shocks, and that policy can directly influence (through e.g. a hiring subsidy or a firing tax). A firm can adjust its number of workers through two channels: hiring and firing. Focusing on the number of hirings and firings would thus be an ideal starting point to study the determinants of unemployment but unfortunately, the variance decomposition approach is based on hazard rates, not gross flows. However, for a firm, choosing the number of new hires and fires is isomorphic to choosing the number of job openings (assuming that they ultimately all get filled) and choosing the percentage of the workforce to be shed, i.e. the job separation rate due to layoffs. Further, an employed worker can decide whether to quit and as a result can influence the job separation rate due to quits. The total job separation rate (due to layoffs

[6]This specification is used in almost all macroeconomic models that introduce equilibrium unemployment through search and matching frictions (see e.g. Pissarides, 2001). I assume a constant returns to scale specification because this is a standard assumption in the search literature. However, the paper's approach goes through with a decreasing or increasing returns to scale matching function.

[7]If JF is endogenously determined by u_t, one could worry that Shimer's (2007) method to recover $\{\bar{f}_t\}$ and $\{\bar{s}_t\}$ is not valid. Indeed, when $f_{t+\tau} = h_0 \left(\frac{v_{t+\tau}}{u_{t+\tau}} \right)^{1-\sigma}$, $f_{t+\tau}$ is not constant over $[t, t+1[$. The differential equation (1) changes and cannot be manipulated as in Section 2. However, I show in the Appendix that by assuming as in Shimer (2007) that, at a monthly frequency, $f_{t+\tau} \simeq \bar{f}_t$, $\forall \tau \in [0, 1[$, the approach still goes through and does not lead to any substantial bias in $\{\bar{s}_t\}$.

and quits) then captures both firms and workers decisions. In the rest of the paper, I will only report the contributions of the total job separation rate and vacancy posting, but in the Appendix, I present a variance decomposition that treats separately the three main decision variables of economic agents: vacancy posting, layoffs and quits.[8]

3.2 Modeling JF with a Cobb-Douglas matching function

To model the job finding rate, I estimate a Cobb-Douglas matching function that can capture movements in the monthly job finding rate. Under Shimer's (2007) assumption that $f_{t+\tau} \simeq \bar{f}_t$ over each month $[t, t+1[$, I can use Shimer's estimate of the job finding rate $\bar{f}_t = -\ln(1-\bar{F}_t)$, and I estimate the following equation

$$\ln \bar{f}_t = (1-\sigma) \ln \frac{v_t}{u_t} + c + \varepsilon_t \tag{6}$$

after detrending all variables with an HP-filter.[9]

Seasonally adjusted unemployment u_t is constructed by the BLS from the Current Population Survey (CPS). More difficult is the choice of a measure for vacancy posting v_t. There are two standard measures of job openings; the Help-Wanted advertising Index (HWI) and the Job Openings and Labor Turnover Survey (JOLTS). The Help-Wanted Index is constructed by the Conference Board and measures the number of help-wanted advertisements in 51 major newspapers. This index is only a proxy for vacancy posting but has the advantage of dating back to 1951, thus providing a long time series. However, this "print" HWI index has become increasingly unrepresentative as advertising over the internet has become more prevalent. In fact, the Conference Board stopped publishing its print HWI in May 2008 and publishes in-

[8]As mentioned in the introduction, I abstract from movements in and out of the labor force.

[9]Davis, Faberman and Haltiwanger (DFH, 2009) study the behavior of vacancies and hirings in JOLTS and find that one in six hires occur outside of the matching function framework, i.e. without a prior vacancy. Regression (6) could then be subject to an omitted variable bias. Denoting z_t the fraction of hires outside the matching function framework, total hires equals $m_t/(1-z_t)$ so that I can write $\ln \bar{f}_t = -\ln(1-z_t) + (1-\sigma)\ln\frac{v_t}{u_t} + c + \varepsilon_t$. Assuming the worse case scenario in which $\left|corr(\ln(1-z_t), \ln\frac{v_t}{u_t})\right| = 1$ and (roughly) estimating the standard-deviation of z_t from DFH, Figure 10 to be at most 0.04, I get a maximal bias for σ of $1.var(\ln(1-z_t)) = 0.012$, suggesting that the omitted variable bias is small.

stead since 2005 a measure of online help wanted advertising.[10] To obtain a consistent measure of Help-Wanted advertising over 1951-2009, in the Appendix, I construct a "composite" index, that combines information on “print” and “online” advertising. JOLTS is produced by the BLS and contains monthly data on job openings from 16,000 establishments since December 2000. Since JOLTS provides a more direct, and arguably better, measure of vacancy posting than HWI, I also construct a job openings index using print-online help wanted advertisements until December 2000 and using JOLTS data thereafter.[11] Figure 1 presents the different measures of vacancy posting, and shows that the two composite indexes track each other remarkably well over the last 10 years.

I first estimate (6) with monthly data and using the composite HWI-JOLTS index from 1951:M01 until 2009:M02. All data were previously detrended with an HP filter. Table 2 presents the result. The elasticity σ is precisely estimated at 0.59, and apart from JF’s high-frequency movements (probably due to measurement errors), a matching function does a very good job at capturing movements in the job finding rate. Indeed, after taking quarterly averages, Figure 2 shows that a matching function tracks the empirical job finding rate very closely. Since JOLTS and HWI are two different dataset, I verify the robustness of the results using only one data source at a time. Further, to make sure that the results are not biased by the strong low-frequency movements in HWI before 1977 that are unrelated to the labor market, I estimate (6) with the print-online help-wanted index over 1977:M01-2009:M02 only. We can see that the estimated σ is unchanged at 0.59. Finally, I use JOLTS data only over 2000:M12-2009:M02 and find a slightly lower σ at 0.57. Encouragingly, these estimates lie in the middle of the plausible range reported by Petrongolo and Pissarides (2001).

A legitimate concern with this regression exercise is that equation (6) may be subject to an

[10] Another problem with the HWI is that it is subject to low-frequency fluctuations that are related only tangentially to the labor market; notably, the decline in print advertising in the 1990s and the 1960s newspaper consolidation that may have increased advertising in surviving newspapers. Fortunately, detrending all series with a low frequency trend (since I am only focusing on business cycle fluctuations) should remove the effect of such secular shifts.

[11] Since JOLTS reports the number of job openings at month’s end, I use v_{t-1}^{JOLTS} as the time t measure for the number of vacancies. This allows me to be consistent with v_t^{HWI}, which measures the total number of help-wanted advertisements from the 14th of the previous month to the 13th of the current month.

endogeneity bias. The use of a monthly frequency and the fact that u_t denotes the beginning of period unemployment rate should minimize the problem, but it is still important to verify that there is no significant bias. To do so, I estimate (6) using lagged values of $\frac{v_t}{u_t}$ as instruments.[12] Encouragingly, Table 2 shows that the endogeneity bias is likely to be small as the coefficient is little changed at 0.58.[13]

The robustness of the results over different measures of vacancies and over different sample periods is promising and suggests that a matching function provides a good approximation of the job finding rate and can be reasonably used to control for the endogeneity of JF. For the rest of the paper, I will use the HWI-JOLTS measure of vacancy posting with a matching function elasticity $\sigma = 0.59$ but the results do not rely on this specific choice.

3.3 Variance decomposition

Writing the steady-state approximation for unemployment (3) at a quarterly frequency (as in Shimer, 2007) and modeling the job finding rate with a matching function, I get

$$u_t^{ss} \equiv \frac{s_t}{s_t + f_t} \simeq \frac{s_t}{s_t + h_0 \left(\frac{v_t}{u_t}\right)^{1-\sigma}} \simeq \frac{s_t}{s_t + h_0 \left(\frac{v_t}{u_t^{ss}}\right)^{1-\sigma}}. \tag{7}$$

where all variables now denote quarterly averages of their monthly counterparts.[14]

This approximation relies on the implicit assumption that movements in s_t have an effect on steady-state unemployment (which is the case by definition) as well as on the job finding rate within the time period, so that the quarterly average of the monthly job finding rate reflects the influence of the job separation rate. Fortunately, in the US, unemployment converges to

[12] Such instruments are valid if the residual is not serially correlated. The Durbin-Watson statistics for regression (1) in Table 1 is 1.83. To verify that serial correlation is definitely not an issue, I performed a GMM regression over 1951-1990 for which the Durbin-Watson statistics is 2.02. Results are unchanged.

[13] An issue that I brushed aside is the timing of the measurements of unemployment, vacancy and the job finding rate. In the Appendix, I present a more rigorous way to address these measurement issues, but estimates of σ are unchanged by these timing considerations.

[14] It is important to note that (7) is only an approximation and does not define steady-state unemployment. Steady-state unemployment is still determined from Shimer's (2007) job finding rate measure. I only use a matching function to approximate JF and isolate movements due to changes in vacancy posting.

its steady-state value quite rapidly as Shimer (2007) showed that steady-state unemployment provides an excellent approximation of next month unemployment. As a result, the dynamic interactions between JS and JF (through the matching function) are likely to be reflected in the *quarterly* (and a fortiori yearly) steady-state decomposition.[15] Moreover, I can track the validity of my approach by looking at the contribution of the residual. Indeed, after log-linearizing (7) and using the fact that $\ln f_t = \ln h_0 + \ln \theta_t^{1-\sigma} + \varepsilon_t$, I can rewrite (4) as

$$d \ln u_t^{ss} = (1 - u_t^{ss}) \left[d \ln s_t - (1-\sigma) \left(d \ln v_t - d \ln u_t^{ss} \right) \right] + \eta_t \tag{8}$$

with η_t the sum of successive approximation errors due to the first–order log-linearization, the use of a matching function to model JF, and the fact that I enter steady-state unemployment inside the matching function.

Rearranging (8), I have

$$d \ln u_t^{ss} = \frac{1 - u_t^{ss}}{1 - (1-\sigma)(1-u_t^{ss})} d \ln s_t - \frac{(1-\sigma)(1-u_t^{ss})}{1-(1-\sigma)(1-u_t^{ss})} d \ln v_t + \eta_t \tag{9}$$

or

$$d \ln u_t = d\tilde{u}_t^{sr} + d\tilde{u}_t^{jf} + \eta_t \tag{10}$$

with $d\tilde{u}_t^{sr} = \frac{1-u_t^{ss}}{1-(1-\sigma)(1-u_t^{ss})} d \ln s_t$ and $d\tilde{u}_t^{jf} = -\frac{(1-\sigma)(1-u_t^{ss})}{1-(1-\sigma)(1-u_t^{ss})} d \ln v_t$. The latter can be interpreted as movements in unemployment solely due to changes in vacancy posting, so that $d \ln \tilde{f}_t = (1-\sigma) d \ln v_t$ captures "exogenous" changes in the job finding rate, or equivalently movements in the job finding rate holding unemployment constant. Henceforth, I will refer to $d\tilde{u}_t^{jf}$ as movements in unemployment due to fluctuations in job openings.

I now proceed with the variance decomposition exercise by using the fact that

$$Var\left(du_t^{ss}\right) = Cov(du_t^{ss}, d\tilde{u}_t^{jf}) + Cov(du_t^{ss}, d\tilde{u}_t^{sr}) + Cov(du_t^{ss}, \eta_t)$$

[15] As a robustness check, I also conducted the variance decompositions at a yearly frequency and found that the results are unchanged.

so that $\beta^{sr} = \frac{Cov(du_t^{ss}, d\tilde{u}_t^{jf})}{Var(du_t^{ss})}$ and $\beta^{sr} = \frac{Cov(du_t^{ss}, d\tilde{u}_t^{sr})}{Var(du_t^{ss})}$ measure the contributions of job separation and the "exogenous" (i.e. independent of unemployment) component of the job finding rate to unemployment's variance.

A back-of-the-envelope calculation can readily give an idea of the revised contribution of the job separation rate when I take into account the endogeneity of JF. With $\sigma \simeq 0.6$ and $u \simeq 0.05$, the endogeneity of JF biases the contribution of JS downwards by 60 percent (from $\frac{1}{1-(1-\sigma)(1-u)} \simeq 1.6$). Instead of a contribution of about 25 percent as reported in Shimer (2007), JS would in fact contribute to about 40 percent, a far from negligible amount.[16]

Using the log-deviation from trend $du_t = \ln\left(\frac{u_t^{ss}}{\underline{u}_t^{ss}}\right)$ where $\underline{u}_t^{ss}$ and $\underline{s}_t^{ss}$ denote the trend component of u_t^{ss} and s_t, I can rewrite (9) as

$$\ln\left(\frac{u_t^{ss}}{\underline{u}_t^{ss}}\right) = \frac{1-\underline{u}_t^{ss}}{1-(1-\sigma)(1-\underline{u}_t^{ss})}\ln\left(\frac{s_t}{\underline{s}_t}\right) - \frac{(1-\sigma)\,(1-\underline{u}_t^{ss})}{1-(1-\sigma)(1-\underline{u}_t^{ss})}\ln\left(\frac{v_t}{\underline{v}_t}\right) + \eta_t. \qquad (11)$$

The first column of Table 3 compares the values of the betas over 1951-2008 with and without controlling for the endogeneity of the job finding probability. Controlling for unemployment fluctuations is important as the contribution of the job separation rate increases from 24 percent to 39 percent.[17] The successive approximations naturally increase the error component in the log-decomposition, and the contribution of the residual amounts to about 5 percent. To evaluate the bias introduced by a matching function, the middle row of Table 3 presents a variance decomposition exercise between JF and JS but using the matching function to model JF. We can see that the use of a matching function increases the contribution of the residual to 4 percent and correspondingly biases downwards the estimate of JF's contribution. As a result, the contribution of vacancy posting is likely to be underestimated and is probably closer

[16] As a robustness check, if I span the plausible matching function elasticities estimated in the literature $0.5-0.7$ (Petrongolo and Pissarides, 2001), the contribution of JS is 10 to 20 percentage points larger after taking into account the endogeneity of JF.

[17] In the Appendix, I extend this approach by using CPS data from the BLS on the reasons for unemployment (layoffs, quits or labor force entrants) over 1968-2004 as used in Elsby & al (2008). I find that layoffs contribute to 45 percent of unemployment fluctuations but quits, being procyclical, lower the contribution of JS by 10 percentage points, a point originally made qualitatively by Elsby et al. (2008).

to 60 than 55 percent. Overall, the residual contribution remains small. This confirms that the matching function does a good job at approximating the job finding rate, and that my approach provides a reasonable framework to evaluate the respective contributions of vacancy posting and layoffs/quits.

Using a first-differenced log-decomposition as in Fujita and Ramey (2009) and using $du_t = \Delta \ln u_t^{ss} = \ln \frac{u_t^{ss}}{u_{t-1}^{ss}}$, I have

$$\Delta \ln u_t^{ss} = \frac{1 - u_{t-1}^{ss}}{1 - (1-\sigma)(1 - u_{t-1}^{ss})} \Delta \ln s_t - \frac{(1-\sigma)\left(1 - u_{t-1}^{ss}\right)}{1 - (1-\sigma)(1 - u_{t-1}^{ss})} \Delta \ln v_t + \eta_t.$$

The second column of Table 3 presents the result. This time, the contribution of JS increases from 40 percent to 63 percent, while the contribution of JF drops to only 35 percent. The contribution of the residual remains small at around 2 percent.

To sum up, controlling for the endogeneity of the job finding rate raises the contribution of JS to unemployment's variance by 60 percent; with a 40/60 split between vacancy posting and job separation for a decomposition in level and a 60/40 split for a decomposition in first-differences. As a result, modeling the job separation probability as acyclical will lead researchers to understate the volatility of unemployment.[18]

3.4 Higher-order moments

While the literature has focused on unemployment's variance to evaluate the importance of the job separation rate, higher-order moments could paint a different picture. Notably, a stylized fact about unemployment is its asymmetric behavior, and a large literature has documented a non-trivial asymmetry in steepness for the cyclical component of unemployment, i.e. that increases are steeper than decreases.[19] To evaluate the respective contributions of job separation

[18] Indeed, Shimer (2005) shows in a very influential paper that the Mortensen-Pissarides (1994) model with a constant job separation rate lacks an amplification mechanism because it generates less than 10 percent of the observed business cycle fluctuations in unemployment given labor productivity shocks of plausible magnitude.

[19] See, among others, Neftci (1984), Delong and Summers (1984), Sichel (1993) and McKay and Reis (2008) for evidence of asymmetry at quarterly frequencies.

and vacancy posting, I extend Fujita and Ramey's (2009) approach to higher-order moments and notably to the concept of skewness.

Let us denote the mean of X as $\mu = E(X)$ and its nth moment $\alpha_n \equiv \frac{E(X-\mu)^n}{(E(X-\mu)^2)^{n/2}}$ for $n \in \mathbb{N}$.

We saw in (10) that changes in (log) unemployment can be written as a sum of components. So, let us assume that $X - \mu$ can be written as a sum of terms so that $X - \mu = \sum_i (X_i - \mu_i)$. By noting that $(X-\mu)^n = \left(\sum_i X_i - \mu_i\right)^n = \sum_i (X-\mu)^{n-1}(X_i - \mu_i)$, I have $E(X-\mu)^n = \sum_i E(X-\mu)_i^{n-1}(X_i - \mu_i)$ so that I can write

$$\alpha_n = \frac{E(X-\mu)^n}{(E(X-\mu)^2)^{n/2}} = \sum_i \frac{E(X-\mu)^{n-1}(X_i-\mu_i)}{(E(X-\mu)^2)^{n/2}}. \tag{12}$$

Dividing (12) by α_n, I get

$$1 = \sum_i \frac{E(X-\mu)^{n-1}(X_i-\mu_i)}{E(X-\mu)^n}$$

and I interpret $\gamma_i = \frac{E(X-\mu)^{n-1}(X_i-\mu_i)}{E(X-\mu)^n}$ as a measure of the contribution of X_i to X's nth moment. Indeed $E(X-\mu)^{n-1}(X_i-\mu_i)$ captures the fraction of $E(X-\mu)^n$ that is due to movements in X_i.

I can now estimate the contributions of vacancy posting and job separation to the steepness asymmetry of unemployment.[20] To do so, I consider the skewness of first-difference log-unemployment. Table 4 shows that over 1955-2008, first-differenced log-unemployment has a skewness coefficient of 1.2, significant at the 5% level.[21] Vacancy posting and JS also present a significant asymmetry in steepness with coefficients of -0.79 and 0.42. Using the

[20] I first detrend unemployment, vacancy and the hazard rates before studying the skewness of first-differenced variables as trends may bias the skewness coefficient.

[21] Over 1951-1954, unemployment experienced very large quarterly movements that dramatically increase the skewness coefficient (by 0.4) and confidence interval. Since the skewness estimate is otherwise stable over 1955-2008, I omit the 1951-1954 time period for clarity of exposition. Nonetheless, my results remain valid over 1951-2008.

log-decomposition (10) and using $du_t = \Delta \ln u_t^{ss} = \ln \frac{u_t^{ss}}{u_{t-1}^{ss}}$, I have

$$\Delta \ln u_t^{ss} = \frac{1-u_{t-1}^{ss}}{1-(1-\sigma)(1-u_{t-1}^{ss})}\Delta \ln s_t - \frac{(1-\sigma)\left(1-u_{t-1}^{ss}\right)}{1-(1-\sigma)(1-u_{t-1}^{ss})}\Delta \ln v_t + \eta_t.$$

so that I can interpret $\frac{E(du_t^{ss})^2 d\tilde{u}_t^{sr}}{E(du_t^{ss})^3}$ and $\frac{E(du_t^{ss})^2 d\tilde{u}_t^{jf}}{E(du_t^{ss})^3}$ as the contributions of the job separation and vacancy posting margins to the skewness of first-differenced unemployment. Table 5 shows that while the job separation rate contributes to less than half of unemployment's variance, this is hardly the case with unemployment asymmetry since the job separation's contribution stands at more than 62 percent. Thus, a model that would not consider fluctuations in the job separation rate would seriously downplay the asymmetric behavior of unemployment. Reassuringly, the contribution of the residual remains low and stands at around 5 percent. A comparison of the first two rows of Table 5 indicates that a matching function biases upwards the contribution of JF as the latter increases from 60 to 63 percent. As a result, the contribution of vacancy posting is likely to be overestimated, and a rough split between job separation and vacancy posting is 60/40.

Table 4 presents another new fact pertaining to the fourth moment of unemployment and its hazard rates. While unemployment has a mild (but significant) negative excess kurtosis (-0.34), vacancy posting and job separation have kurtosis of opposite signs. Vacancies present a large negative excess kurtosis (-0.94) but JS presents a positive excess kurtosis (0.54). Recall that a high kurtosis distribution such as that of JS has a sharper peak and longer, fatter tails, i.e. extreme values are drawn more often than with a normal distribution. This finding is not surprising if we think of job separation as capturing (among other things) bursts of layoffs. On the other hand, a low kurtosis distribution such as that of vacancies has a more rounded peak and shorter thinner tails, i.e. fewer extreme values. To visualize the distribution of steady-state unemployment, vacancy posting and the job separation rate, Figure 3 plots the kernel density estimates of these variables using a Gaussian kernel with optimal bandwidth. The dashed lines represent the corresponding (i.e. mean and variance) normal distributions. While unemployment's distribution is very close to being normal, this is hardly the case for vacancy posting and job separation. Vacancy posting has almost a bimodal distribution with rapidly decreasing tails but the job separation rate has a small mass of points around the mean and very fat tails.

Looking at the contributions of each hazard rate, Table 5 shows that vacancy posting and job separation contribute in roughly equal proportion to unemployment's fourth moment, with a slight advantage for vacancy posting. Given the lower contribution of JS to unemployment's variance, the mild negative kurtosis of unemployment despite the large negative kurtosis of vacancy posting is consistent with an interpretation of job separation influencing unemployment through rare but violent episodes of job separation. The contribution of the residual amounts to less than 4 percent, and the second row of Table 5 indicates that the use of a matching function biases the contribution of JF downwards. As a result, the split between job separation and vacancy posting is roughly 45/55. While only indicative, this fourth-moment decomposition suggests that vacancy posting drives unemployment during normal times but that job separation is responsible for rare but violent fluctuations in unemployment.

4 The contributions of vacancy posting and job separation at business cycle turning points

The evidence from the kurtosis decomposition exercise suggests that vacancy posting drives unemployment during normal times but that job separation is responsible for rare but violent fluctuations in unemployment. To explore this idea further, I depart from an average decomposition to analyze the relative contributions of the job separation rate and vacancies around the turning points of unemployment fluctuations.

After detrending unemployment using an HP-filter with $\lambda = 10^5$, I follow McKay and Reis (2008) and identify highs and lows in unemployment using the algorithm of Bry and Boschan

(1971). Figure 4 plots the steady-state unemployment rate with identified turning points.[22]

The first rows of Figure 5 and 6 plot the average dynamics of the log-deviation from trend of steady-state unemployment, the job separation rate, and the job finding rate in a window of 3 and 6 quarters before and after the highs and lows of unemployment.[23] As first shown by Elsby et al. (2009) with NBER recessions dates, an interest of this approach is that the log-decomposition (4) allows us to directly observe the relative contributions of JS and JF to unemployment fluctuations. The second rows of Figure 5 and 6 display the same average dynamics but using the log of vacancy times $(1-\sigma)$ instead of JF.[24] From (11), we can directly observe the relative contributions of job separation and vacancy posting as $(1-\sigma)d\ln(v)$ corresponds to movements in unemployment caused by changes in vacancy posting.

A first observation is that, while the previous section showed that vacancy posting was, on average, the most important contributor of unemployment fluctuations, this is hardly the case at business cycle turning points. Around highs and lows, JS is the prime determinant of movements in unemployment. Without controlling for the endogeneity of JF, the results shown in Figure 6 are in line with Elsby et al's (2009) findings for NBER recessions: once unemployment reaches a low, JS is responsible for most of the initial increase in unemployment, but after two quarters JF becomes the dominant contributor of the increase in unemployment. The same conclusion holds for unemployment highs. However, the second row of Figure 6 shows that when I consider only the "exogenous" component of JF, job separation accounts for more than 50 percent of unemployment movements for as much as 6 quarters after a high or a low, and for almost all of the initial response. Interestingly, this result is consistent with the decomposition of unemployment's fourth moment in the previous section, which suggests that

[22]See McKay and Reis (2008) for a presentation of possible methods to identify the peaks and troughs of a series. All the results are robust to using the alternative methods reported in McKay and Reis (2008).

[23]For each quarter j around an unemployment turning point t_0, I plot $\left[\ln\left(\frac{u^{ss}_{t_0+j}}{\bar{u}^{ss}_{t_0+j}}\right) - \ln\left(\frac{u^{ss}_{t_0}}{\bar{u}^{ss}_{t_0}}\right)\right]$, $\left[\left(1-\bar{u}^{ss}_{t_0+j}\right)d\ln s_{t_0+j} - \left(1-\bar{u}^{ss}_{t_0}\right)d\ln s_{t_0}\right]$, and $-\left[\left(1-\bar{u}^{ss}_{t_0+j}\right)d\ln f_{t_0+j} - \left(1-\bar{u}^{ss}_{t_0}\right)d\ln f_{t_0}\right]$. According to (4), the first term is the sum of the last two so that, for each quarter t around a turning point T, Figure 5 and 6 show the contributions of JF and JS to deviations of unemployment from its low or high.

[24]Comparing carefully the two rows of Figure 4 (or Figure 5), the two unemployment rates are not exactly equal. This small difference comes from the approximation error when modeling JF with a matching function.

extreme values of unemployment are due to the job separation rate. Looking at the contribution of the residual, the approximation is relatively good three quarters before and after a turning point but deteriorates slightly thereafter. However, assigning all of the residual's contribution to vacancy posting (a worst case scenario for JS) does not change the main conclusion; JS still accounts for more than 50 percent of unemployment movements a year after a high or low.

Two other observations are worth noting. First, the asymmetric nature of unemployment is clearly apparent in Figure 5 and 6 as unemployment increases faster than it decreases. This asymmetry can be linked to the asymmetric response of JS. Vacancy posting reacts slowly, and the slope of vacancy posting is much weaker than that of job separation in the first quarters after a turning point. Second, after unemployment highs, vacancies lag job separation by a quarter. This is in line with Fujita and Ramey (2009), who find that the job separation rate lags the job finding rate.

An implication of these last findings is that ignoring the job separation margin when modeling unemployment will lead researchers to underestimate the breadth and speed of adjustments in unemployment around turning points.

5 Conclusion

A decomposition of unemployment fluctuations between the job finding rate and the job separation rate is difficult to interpret because of the dynamic interactions linking the two hazard rates. In this paper, I propose an alternative decomposition between vacancy posting and the job separation rate.

After isolating the fluctuations in the job finding rate due solely to changes in firms' recruiting efforts, I find that the contribution of the job separation rate to unemployment's variance is close to 40 percent instead of 25 percent using Shimer's (2007) methodology. I also extend Shimer (2007), Elsby et al (2009) and Fujita and Ramey (2009) variance decomposition to higher-order moments, and I find that job separation contributes to about 60 percent of unemployment steepness asymmetry, a stylized fact of the jobless rate. Further, while vacancy posting is, on average, the more important contributor of unemployment fluctuations, the opposite is true around business cycle turning points, when job separation is responsible for most of unemployment movements.

These results imply that modeling the job separation margin as acyclical will lead researchers to (i) understate the volatility of unemployment, (ii) seriously downplay the asymmetric behavior of unemployment, and (iii) underestimate the breadth and speed of adjustments in unemployment around business cycle turning points.

Finally, the dynamic interactions between the job separation rate and the job finding rate are inconsistent with the standard MP model and suggest that the canonical model is incomplete. One extension would be to treat vacancy posting as a state variable. For example, an MP model with sunk cost in vacancy creation as in Fujita and Ramey (2007) could explain why the job separation rate Granger-causes the job finding rate.[25] Another possibility would be time to build in vacancy posting. Interestingly, in such extensions, a variance decomposition of unemployment should focus on vacancy posting, as in the present paper, rather than the job finding rate, since only vacancy posting could be directly linked to exogenous driving processes.

[25] Fujita and Ramey (2007) do not allow for an endogenous separation rate.

Appendix

A1 The timing of u_t, v_t, and f_t

An important issue when using measures for unemployment, vacancy posting and job finding probability concerns the precise definition of each variable. In particular, while some variables are beginning or end of month values, others are monthly averages.

In the CPS, the BLS surveys the number of unemployed during the reference week, defined as the week including the 12th day of the month. The Help-Wanted Index v_t^{HWI} measures the total number of advertisements (print or online) from the 14th (t)of the month to the 13th of next month ($t+1$). JOLTS, on the other hand, indicates the number of job openings v_t^{JOLTS} on the last day of month t. Finally, Shimer's (2007) definition of $\bar{F}_t$ implies that $\bar{F}_t$ measures the average job finding probability between two unemployment measurement dates, i.e. between the week including the 12th of next month and the week including the 12th of the current month.

To be as consistent as possible with these measurement dates, the average job finding probability should depend on the average unemployment rate and the average number of posted vacancy between two reference weeks. Since u_t measures the unemployment rate during the first reference week, the correct measure of unemployment inside the matching function should be $\frac{1}{2}(u_t + u_{t+1})$. Since v_t^{HWI} already corresponds to an average over a period and v_t^{JOLTS} measures the number of job openings at a date roughly in between two reference weeks, v_t^{JOLTS} corresponds to v_t^{HWI} as those two measures would be equal if the number of job openings remained constant in between two reference weeks.

As a result, a more consistent regression to estimate a matching function would be

$$\ln \bar{f}_t = (1-\sigma) \ln \frac{v_t}{\frac{1}{2}(u_t + u_{t+1})} + c + \varepsilon_t \tag{13}$$

after detrending all variables with an HP-filter. Of course, such a regression is clearly subject to an endogeneity bias as u_{t+1} is a function of $\bar{f}_t$ Therefore, to estimate (13), I use GMM as in column (4) of Table 2. Encouragingly, the regression results are virtually identical to the ones obtained using (6).[26]

A2 A composite Help-Wanted index

To obtain a consistent measure of Help-Wanted advertising over 1951-2009, I refine a method proposed by Fallick (2008) and build an index that combines information on "print" and "online" Help-Wanted advertising.

Denote respectively $P_t^{\#}$ and $O_t^{\#}$ the number of print help-wanted advertisements and online help-wanted advertisements. The total number of advertisements (print and online) $H_t^{\#}$ is then given by $H_t^{\#} = P_t^{\#} + O_t^{\#}$, and $s_t^p = \frac{P_t^{\#}}{P_t^{\#}+O_t^{\#}}$ is the share of print help-wanted advertising in total advertising. Further, denote H_t the composite Help-Wanted advertising index, P_t the print index, and O_t the online index. The indexes are defined with respect to some base year t_0, and I have $P_t = \frac{P_t^{\#}}{P_{t_0}^{\#}}$ and $O_t = \frac{O_t^{\#}}{O_{t_0}^{\#}}$.

To build the composite index, I consider four separate periods:

1) Until 1995:

I assume that there is no online job posting up until 1995. As a result, $H_t^{\#} = P_t^{\#}$ and I normalize the composite index so that $H_t = P_t$ over 1951-1994.

2) January 1995-May 2005:

Over that period, the print HWI exhibits a clear downward trend (see Figure 1), and the online HWI is not observable. To build the composite index, I make two assumptions that I can verify ex-post. First, as in Fallick (2008), I interpret the trend in print HWI as a secular decline in the share of newspaper advertising due to the emergence of the web and online advertising. Second, I assume that there are no cyclical fluctuations in the ratio of print advertising to online advertising. In that case, the behavior of s_t^p is entirely explained by the downward trend in print advertising. With those two assumptions, I can estimate the share of print advertising from $\bar{s}_t^p$; the ratio of the trend in the print HWI to the value of that trend in

[26] The results are available upon request.

1994.[27] I can then recover $O_t^{\#}$ from the definition of s_t^p with $O_t^{\#} = P_t^{\#}\frac{1-s_t^p}{s_t^p}$. The total number of job advertisements is $H_t^{\#} = P_t^{\#} + P_t^{\#}\frac{1-s_t^p}{s_t^p} = \frac{P_t^{\#}}{s_t^p}$, and starting in January 1995, I construct the composite index from $d\ln H_t = d\ln H_t^{\#} = d\ln\frac{P_t^{\#}}{\bar{s}_t^p} = d\ln\frac{P_t}{\bar{s}_t^p}$.

3) June 2005-May 2008:

Over that (short) period, both the print and online HWI are available, and I can combine the two series. Log-linearizing $H_t^{\#} = P_t^{\#} + O_t^{\#}$, I get $d\ln H_t^{\#} = s_{t-1}^p d\ln P_t^{\#} + (1-s_{t-1}^P)d\ln O_t^{\#}$ to a first order. Starting in June 2005, I can then construct the composite index from $d\ln H_t = \bar{s}_{t-1}^p d\ln P_t + (1-\bar{s}_{t-1}^p)d\ln O_t$.[28]

Importantly, I can use the fact that the print HWI and the online HWI are simultaneously observable to assess the accuracy of $\bar{s}_t^p$, the estimate of s_t^p used to construct the composite index. After log-differencing $O_t^{\#} = P_t^{\#}\frac{1-s_t^p}{s_t^p}$, I can infer a value $\hat{s}_t^p$ of the share of print advertising from $d\ln\left(\frac{s_t^p}{1-s_t^p}\right) = d\ln(P_t) - d\ln(O_t)$. Figure 7 compares $\hat{s}_t^p$ with $\bar{s}_t^p$. The two series display a similar downward trend, which indicates that the trend in print HWI does a good job at capturing the behavior of s_t^p. Moreover, $\hat{s}_t^p$ fluctuates little around its trend, thereby confirming my initial assumption that the ratio of print advertising to online advertising is constant throughout the cycle.

4) After June 2008:

Since only the online HWI is observable after June 2008, I use the estimate $\bar{s}_t^p$ and the fact that $P_t^{\#} = O_t^{\#}\frac{s_t^p}{1-s_t^p}$ to get $H_t^{\#} = \frac{O_t^{\#}}{1-s_t^p}$. I then construct the composite index from $d\ln H_t = d\ln\frac{O_t^{\#}}{1-s_t^p}$.

[27] I use a quartic polynomial trend on monthly data over 1951-2008 to capture the trend in print HWI. This particular filter appears to be doing a good job at capturing a decline in the trend of HWI after 1994, and as I show below, that trend is consistent with the joint behavior of print and online HWI over 2005-2008.

[28] Looking at Figure 1, one may worry that the noise-to-signal ratio of detrended print HWI is quite high in the last years of the index. To avoid that potential issue, an alternative is to rely on the estimate $\bar{s}_t^p$ and ignore P_t. Using $P_t^{\#} = O_t^{\#}\frac{s_t^p}{1-s_t^p}$, I get $H_t^{\#} = \frac{O_t^{\#}}{1-s_t^p}$, and I can construct the composite index from $d\ln H_t = d\ln\frac{O_t^{\#}}{1-s_t^p}$. Results are little changed.

A3 Identifying $\{s_t\}$ with an endogenous job finding rate

One could worry that because of the endogeneity of JF, Shimer's (2007) method to recover $\{\bar{f}_t\}$ and $\{\bar{s}_t\}$ is not valid. Indeed, when $f_{t+\tau} = h_0 \left(\frac{v_{t+\tau}}{u_{t+\tau}}\right)^{1-\sigma}$, $f_{t+\tau}$ is not constant over $[t, t+1[$, and the differential equation satisfied by unemployment changes to take the form

$$\frac{du_{t+\tau}}{d\tau} = \bar{s}_t \left(1 - u_{t+\tau}\right) - f_{t+\tau} u_{t+\tau}.$$

In that case, I cannot manipulate (1) as in Section 2 to recover $\{\bar{f}_t\}$ and $\{\bar{s}_t\}$. Fortunately, the approach still goes through if, within each month, movements in $f_{t+\tau}$ over $[t, t+1[$ are negligible compared to f_t's start of the period value. Indeed, if $f_{t+\tau} = f_t + \varepsilon_{t+\tau}$ with $\varepsilon_{t+\tau} << f_t$, one can reasonably approximate the instantaneous job finding rate with the average one so that $f_{t+\tau} \simeq \bar{f}_t$. Under this approximation, the differential equation reduces to (1) and one can recover $\bar{s}_t$ as in Shimer (2007).

I now show that this approximation is reasonable as it does not lead to any substantial bias in $\{\bar{s}_t\}$. Instead of assuming that $f_{t+\tau}$ remains constant over $[t, t+1[$, I make the weaker assumption that only $v_{t+\tau}$ is constant over $[t, t+1[$ and equals v_t. This assumption is consistent with the definition of v_t^{HWI}; the total number of vacancies over $[t, t+1[$ (see Appendix A1). The law of motion for unemployment (1) now takes the form

$$\begin{aligned}\frac{du_{t+\tau}}{d\tau} &= \bar{s}_t \left(1 - u_{t+\tau}\right) - f_{t+\tau} u_{t+\tau} \\ &= \bar{s}_t \left(1 - u_{t+\tau}\right) - h_0 v_t^{1-\sigma} u_{t+\tau}^{\sigma}\end{aligned}$$

Similarly to Shimer (2007), I then solve this differential equation for different values of $\bar{s}_t$ until the solution at time $t+1$ equals u_{t+1}. In Figure 8, I compare the estimates of s_t obtained with and without assuming constant hazard rates. As we can see, both estimates are extremely similar suggesting that the approximation $f_{t+\tau} \simeq \bar{f}_t$ over $[0, 1[$ is reasonable as it does not lead to any substantial bias in $\{\bar{s}_t\}$.[29]

[29] This approach is quite sensitive to the parameterization of the matching function and the value of σ, but it

A4 The contributions of layoffs and quits

In this section, I study the separate contributions of layoffs and quits to unemployment's variance by using CPS data from the BLS on the reasons for unemployment (layoffs, quits or labor force entrants) over 1968-2004 as in Elsby et al. (2009). Denoting u_t^λ, u_t^q and u_t^e the unemployment rates by reason, I have $u_t = u_t^\lambda + u_t^q + u_t^e$ and $d\ln u_t = \omega_\lambda d\ln u_t^\lambda + \omega_q d\ln u_t^q + \omega_e d\ln u_t^e$, with $u_t^\lambda = \frac{s_t^\lambda e_t}{f_t^\lambda}$, $u_t^q = \frac{s_t^q e_t}{f_t^q}$ and $u_t^e = \frac{s_t^e i_t}{f_t^e}$ where e_t is the employment rate and i_t the labor force participation rate. Looking at Elsby et al. (2009) decomposition, we can see that business cycle fluctuations in e_t and i_t are small compared to cyclical fluctuations in the hazard rates, and that fluctuations in s_t^e are small compared to movement in the other inflows rates (see Elsby et al. (2009), Figures 9 & 11). As a result, I can write the following approximation

$$\begin{aligned}
d\ln u_t^{ss} &= \omega_\lambda d\ln s_t^\lambda - \omega_\lambda d\ln f_t^\lambda + \omega_q d\ln s_t^q - \omega_q d\ln f_t^q \\
&\quad + \omega_e d\ln s_t^e - \omega_e d\ln f_t^e + (\omega_e + \omega_q) d\ln e_t + \omega_e d\ln i_t \\
&\simeq \omega_\lambda d\ln s_t^\lambda + \omega_q d\ln s_t^q - \omega_\lambda d\ln f_t^\lambda - \omega_q d\ln f_t^q - \omega_e d\ln f_t^e \\
&\simeq \omega_\lambda d\ln s_t^\lambda + \omega_q d\ln s_t^q - d\ln f_t
\end{aligned}$$

And using a matching function to model the job finding rate, I can write

$$\Delta \ln u_t^{ss} \simeq \frac{\omega_\lambda \Delta \ln s_t^\lambda + \omega_q \Delta \ln s_t^q - (1-\sigma)\Delta \ln (v_t)}{1 - (1-\sigma)(1 - u_{t-1}^{ss})}$$

and

$$\ln \frac{u_t^{ss}}{\underline{u}_t^{ss}} \simeq \frac{\omega_\lambda \ln \ln \left(\frac{s_t}{\underline{s}_t}\right) + \omega_q \Delta \ln \ln \left(\frac{s_t}{\underline{s}_t}\right) - (1-\sigma)\Delta \ln \left(\frac{v_t}{\underline{v}_t}\right)}{1 - (1-\sigma)(1 - \underline{u}_t^{ss})}.$$

Using this extended methodology, I find that layoffs contribute to 45 percent of unemployment fluctuations but quits, being procyclical, lower the contribution of JS by 10 percentage points, a point originally made qualitatively by Elsby et al. (2009). The contribution of vacancy posting is 63 percent, close to that reported in Table 3 despite the shorter time period.

allows me to verify that assuming $f_{t+\tau} \simeq \bar{f}_t$ has almost no consequences on the estimation of $\{s_t\}$.

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Table 1: Granger causality tests, 1951:Q1-2008:Q4

Hypothesis Test	p-value in parenthesis (1 lag)	p-value in parenthesis (2 lags)	p-value in parenthesis (3 lags)
JS does not Granger-cause JF?	No (0.01)	No (6.10^{-13})	No (2.10^{-12})
JF does not Granger-cause JS?	Yes (0.49)	No (1.10^{-3})	No (2.10^{-4})

Table 2: Estimating the matching function from Shimer's Job Finding rate

Dependent variable:	*f*	*f*	*f*	*f*
Sample	1951:M1-2009:M02	1977:M1-2009:M02	2000:M12-2009:M02	1951:M1-2009:M02
	(1)	(2)	(3)	(4)
Regression	Composite index: HWI -- JOLTS	Help-Wanted Index	JOLTS	Composite index: HWI -- JOLTS
Estimation	OLS	OLS	OLS	GMM
σ	0.59***	0.59***	0.57***	0.58***
	(0.01)	(0.01)	(0.02)	(0.02)
R^2	0.81	0.81	0.73	--

Notes: All regressions include a quartic trend. Standard-errors are reported in parentheses. For equation (4), 3 lags used for instruments.

Table 3: Contribution of JF and JS to unemployment variance, 1951-2008

	Variance			Variance		
	β^{JS}	β^{JF}	β^{η}	$\beta^{d(JS)}$	$\beta^{d(JF)}$	β^{η}
Matching fct°: No Control Endog: No	24.4%	75.9%	-0.3%	39.6%	59.6%	0.8%
Matching fct°: Yes Control Endog: No	24.2%	71.8%	4.0%	39.6%	59.2%	1.2%
Matching fct°: Yes Control Endog: Yes	39.3%	55.4%	5.3%	63.4%	34.8%	1.9%

Notes: "Matching fct°" indicates whether I use Shimer's (2007) estimate for *jf* or if I instead model *jf* using a matching function (with a matching elasticity σ=0.59). "Control Endog" indicates whether *f* captures all movements in JF or only those due to changes in vacancies.

Table 4: Higher-order moments of unemployment and hazard rates, 1955-2008

	u^{ss}	v	JS
Skewness	1.21**	-0.79**	0.42**
	(0.53)	(0.24)	(0.09)
Kurtosis	2.66	2.06**	3.54**
	(1.16)	(0.40)	(1.40)

Notes: All variables are expressed in log. All variables are detrended with an HP filter ($\lambda=10^5$).). Newey-West standard errors are reported in parentheses and ** indicates significance at the 5% level. The Skewness is measured with variables in first-difference while the Kurtosis is measured with variables in levels. The job finding rate is modelled with σ=0.59.

Table 5: Contribution of JF and JS to higher-order moments of unemployment, 1955-2008

	Skewness			Kurtosis		
	$\gamma^{d(JS)}$	$\gamma^{d(JF)}$	γ^{η}	γ^{JS}	γ^{JF}	γ^{η}
Matching fct°: No Control Endog: No	38.8%	60.1%	1.1%	27.4%	73.1%	-0.4%
Matching fct°: Yes Control Endog: No	38.8%	63.5%	-2.3%	27.4%	69.7%	3.0%
Matching fct°: Yes Control Endog: Yes	62.5%	42.7%	-5.2%	44.0%	52.5%	3.5%

Notes: "Matching fct°" indicates whether I use Shimer's (2007) estimate for jf or if I instead model jf using a matching function (with a matching elasticity σ=0.59). "Control Endog" indicates whether f captures all movements in JF or only those due to changes in vacancies. The Skewness is measured with variables in first-difference while the Kurtosis is measured with variables in levels.

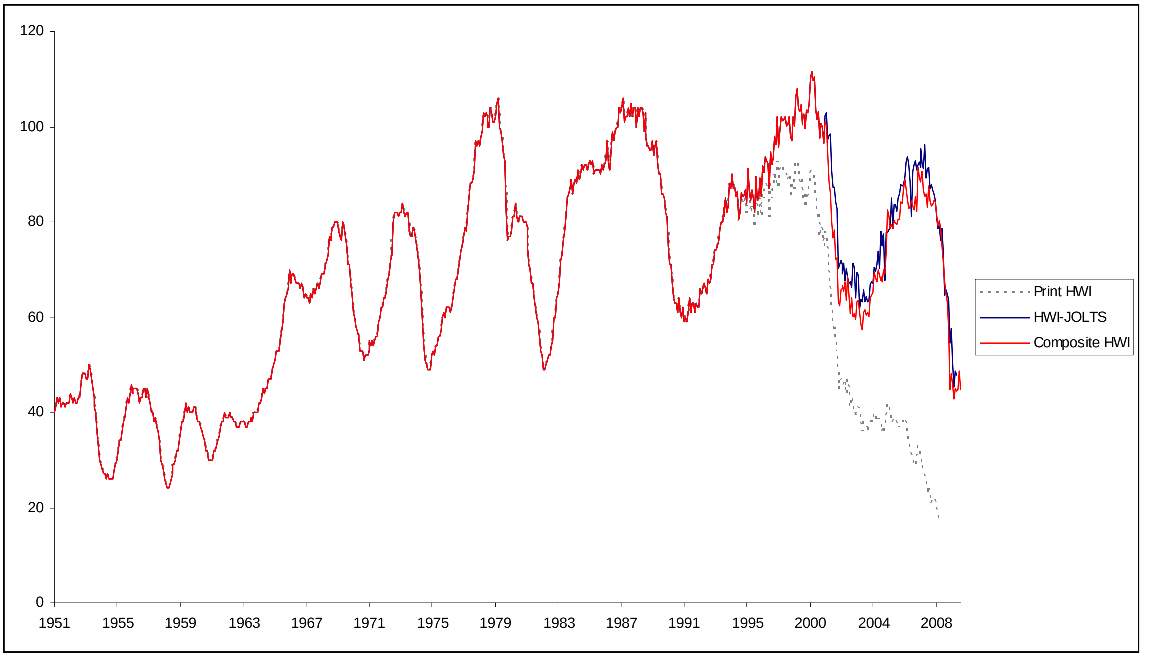

Figure 1: Different indexes of vacancy posting, 1951M01-2009M09.

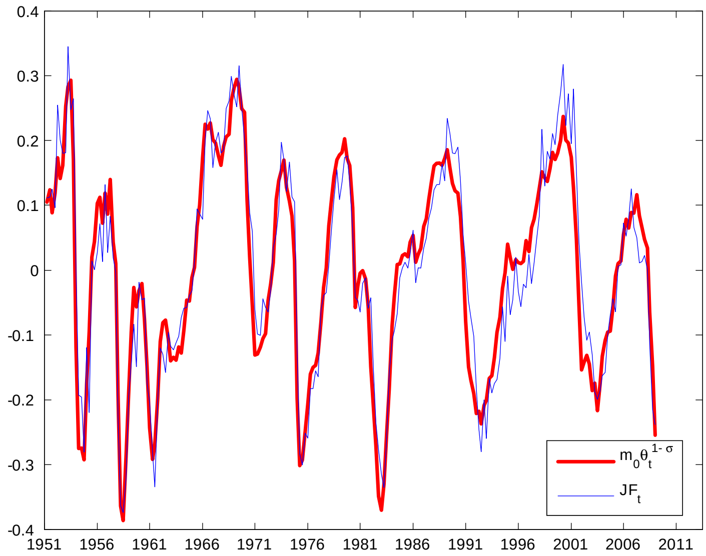

Figure 2: Empirical and model Job Finding rate.

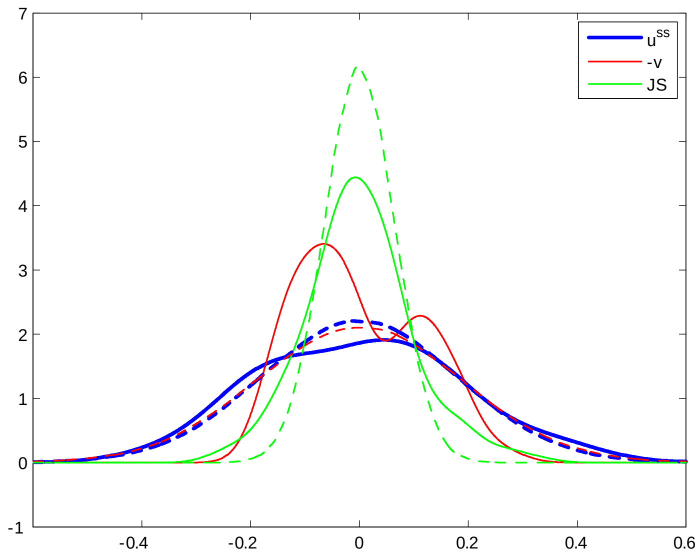

Figure 3: Kernel density estimates (Gaussian kernel) for steady-state unemployment, vacancy posting and the job separation rate. Dotted-lines represent the corresponding normal distributions. All variables are logged and detrended with an HP-filter($\lambda = 10^5$).

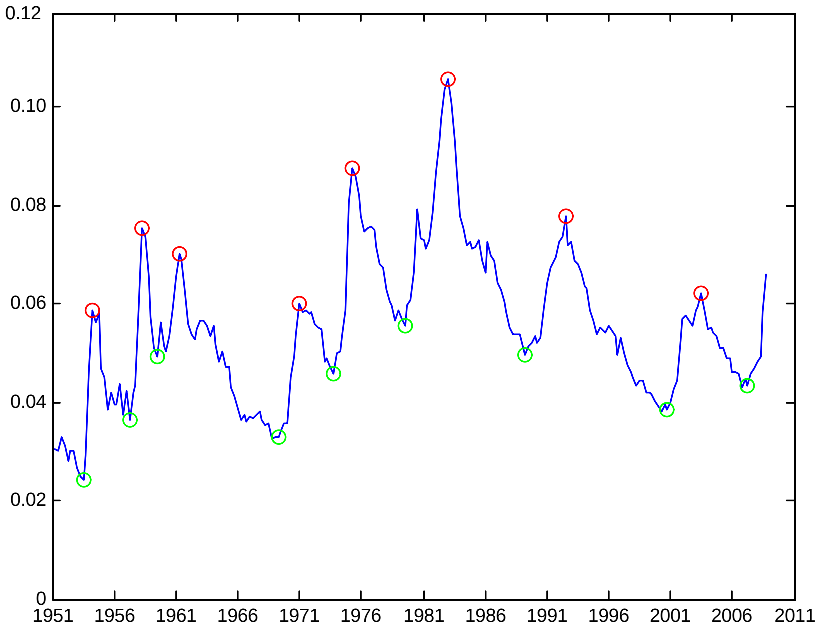

Figure 4: Steady-state unemployment with identified highs and lows, 1951-2008.

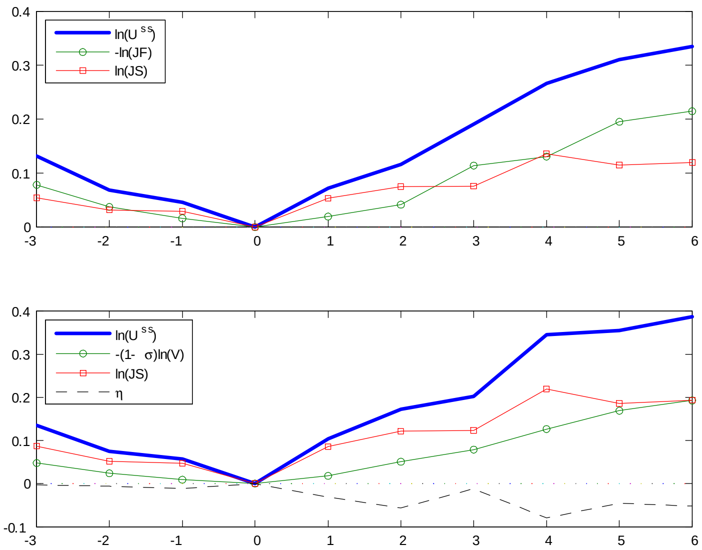

Figure 5: Average business cycle dynamics for steady-state unemployment, the job separation rate, the job finding rate, vacancies, and the residual near unemployment lows. 1951-2008.

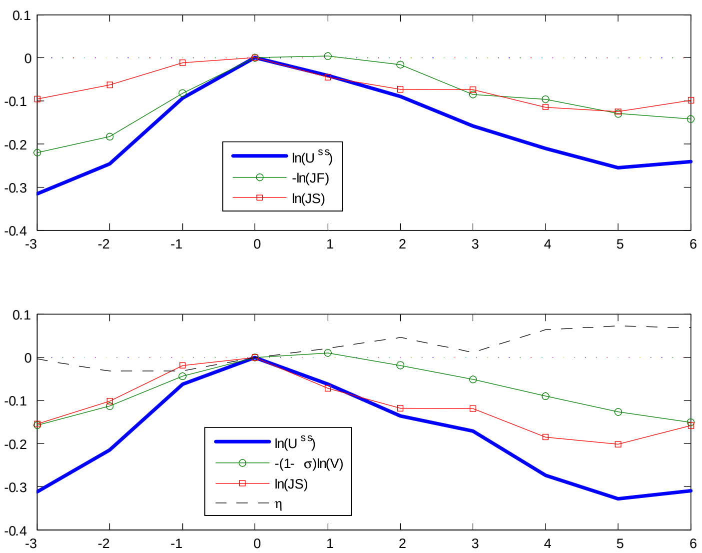

Figure 6: Average business cycle dynamics for steady-state unemployment, the job separation rate, the job finding rate, vacancies, and the residual near unemployment highs. 1951-2008.

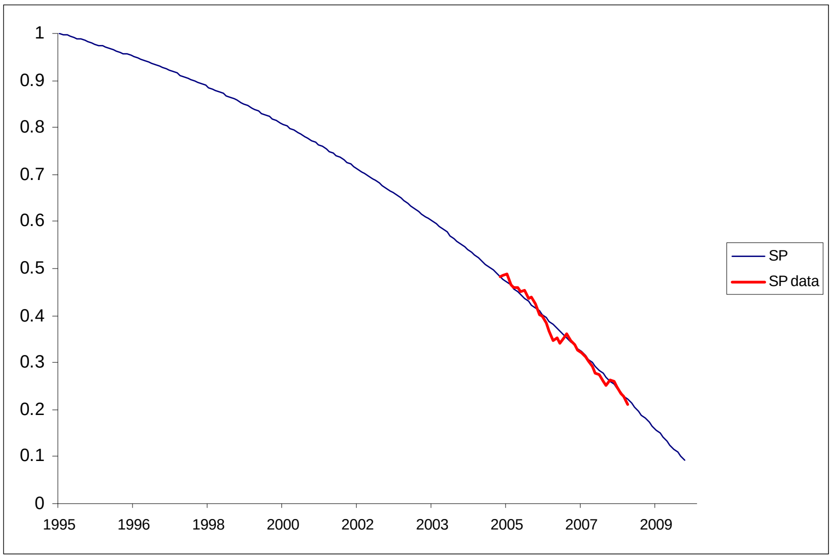

Figure 7: The share of print advertising in total job advertising over 1995-2009. "SP" is the ratio of the trend in print HWI to the value of that trend in 1994. "SP data" is the share of print advertising implied by the behavior of print HWI and online HWI over June 2005-May 2008.

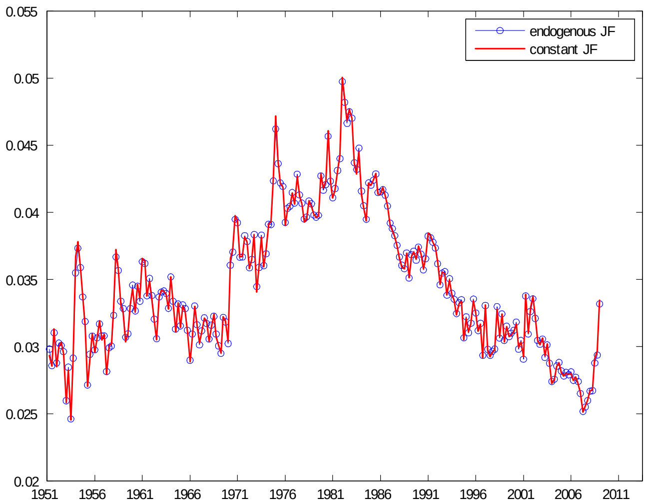

Figure 8: Estimates of the job separation rate with and without assuming $f_{t+\tau} = f_t$ over $[t, t+1[$.