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Please address correspondence to
Banco de Portugal, Economics and Research Department
Av. Almirante Reis 71, 1150-012 Lisboa, Portugal
T +351 213 130 000 | estudos@bportugal.pt

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Zooming the Ins and Outs of the U.S. Unemployment

Pedro Portugal
Banco de Portugal
NOVA School of Business and Economics

António Rua
Banco de Portugal
NOVA School of Business and Economics

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Abstract
To better understand unemployment dynamics it is key to assess the role played by job creation and job destruction. Although the U.S. case has been studied extensively, the importance of job finding and employment exit rates to unemployment variability remains unsettled. The aim of this paper is to contribute to this debate by adopting a novel lens, wavelet analysis. We resort to wavelet analysis to unveil time- and frequency-varying features regarding the contribution of the job finding and job separation rates for the U.S. unemployment rate dynamics. Drawing on this approach, we are able to reconcile some apparently contradictory findings reported in previous literature. We find that the job finding rate is more influential for the overall unemployment behavior but the job separation rate also plays a critical role, especially during recessions.

JEL: C10, E24, E32

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E-mail: pportugal@bportugal.pt; antonio.rua@bportugal.pt

1. Introduction

The unemployment rate is the most conspicuous variable used to characterize the state of the labor market. In essence, it measures the fraction of unemployed individuals among labor force participants, at a given moment. In this sense, the unemployment rate is what epidemiologists call a prevalence rate - the fraction of individuals with a disease among the population at risk. Being a rate that reflects a snapshot, the unemployment rate is not informative regarding the risk of being unemployed because it compounds unemployed workers with different (elapsed) unemployment durations.

To overcome this limitation, the unemployment rate, like any prevalence rate, can be defined as a combination of the incidence rate and the mean duration in the state. The incidence rate is simply the fraction of new cases (recently unemployed) over the population at risk at a given period of time. The mean duration simply reflects the probability of exiting the state in the same period of time.

The notions of incidence and mean duration are useful not only to infer about the nature of the labor market but also to better understand its dynamics, in particular, its cyclical fluctuations. Indeed, similar prevalence rates can be generated by a high incidence rate and a short mean duration (take, for example, the prevalence rate of influenza, or the U.S. unemployment rate) or by a low incidence and a high mean duration (for example, the prevalence of pneumonia or the Portuguese unemployment rate). Over time, it is very revealing to show whether it is the incidence rate or the mean duration that is driving the trends and fluctuations around those trends.

Not surprisingly, economists have made great efforts to disentangle the role of incidence and mean duration, or equivalently, job separation probability and job finding probability, or more generally, inflows into unemployment and outflows from unemployment, driving the cyclical behavior of unemployment (Sider, 1985; Blanchard and Diamond, 1990; Fujita and Ramey, 2009; Shimer, 2012; Elsby *et al.* 2009). Knowing which rate dominates the cyclical behavior of the unemployment rate has important implications for understanding the nature of business cycles and, consequently, for highlighting the necessary features of the macroeconomic models.

Thinking about the determinants of job finding probability is equivalent to considering the determinants of the duration of unemployment. The duration of unemployment depends upon the hiring decisions of the firms and the search strategies of the unemployed. Whereas there is a plethora of empirical research regarding the job search of the unemployed, the evidence on hiring decisions is much thinner. It may be useful to conceptually distinguish between factors that affect trends from the ones that may lie behind the cyclical behavior of job finding probability. The aging of the working population and its increasing feminization may partially explain the increasing role of job finding probability (Abraham and Shimer, 2001). The generosity of the unemployment system is a key variable determining job finding probability and its role is amplified during recessions in economies that automatically extend the duration of benefits during (severe) recessions (Hagedorn *et al.*, 2013; Farber and Valleta, 2015). Hiring costs surely influence hiring decisions, as do (expected) firing costs, should the event of a dismissal materialize. If hiring costs (screening, training, etc.) are essentially non-fixed, one should observe smooth and persistent hiring rates (Hamermesh, 1996). Finally, limitations to wage negotiations, such as the presence of mandatory minimum wages or downward nominal wages, may exacerbate the cyclicality of the job finding probability (for example, through pent-up wage deflation), especially during low-inflation regimes (Carneiro *et al.*, 2014).

The determinants of the job separation probability are, of course, the determinants of job duration. Among job separations it may be useful to distinguish between voluntary (quits) and non-voluntary (dismissals). Quits behave pro-cyclically but dismissals are countercyclical (Hall and Lilien, 1986). Whereas it may be argued that the two types of separations counteract each other's cyclicality, in practice, the cyclical behavior of the job separation probability is largely driven by non-voluntary separations. Firing costs, of course, are likely to play a critical role driving job separation probability. High firing costs engender sclerotic labor markets with low job separation and job finding rates (Blanchard and Portugal, 2001). If firing costs are, to a large extent, non-convex, labor adjustments are going to be lumpy, short-lived, and bunched (Hamermesh, 1989; Caballero and Hammour, 1996). Furthermore, high firing costs may translate into lengthy lower hiring rates if firms take advantage of their natural attrition to avoid incurring termination costs, such as severance payments. There are other factors that may influence the behavior of job separation probability. Wage setting institutions, nevertheless, are more likely to affect unemployment through the determination of entry wages rather than the wages of those workers already employed (Pissarides, 2009).

Being as it may, there is no consensus on the relative empirical importance of the job finding and separation rates over the U.S. business cycle. In contrast with previous thinking, Hall (2005) and Shimer (2012) have recently argued that the separation rate is roughly acyclical, so that the emphasis should be put on the job finding rate. In particular, Hall (2005) finds that the separation rate is relatively constant, whereas the job finding rate presents high variability at low and business cycle frequencies. Such findings are reinforced by Shimer (2012), who concludes that the job finding probability accounts for 77 per cent of U.S. unemployment variability, whereas movements in the employment exit probability account for only 24 per cent for the period from 1948 to 2010, being quantitatively irrelevant during the last two decades. Robert Shimer also shows that these results are not due to compositional changes in the pool of searching workers, nor are they due to flows of workers in and out of the labor force.

In contrast, through a formal decomposition of unemployment variability and resorting to alternative statistical filters, Fujita and Ramey (2009) find that fluctuations in the separation rate contribute substantially to unemployment changes. Using Shimer's data, they find that the separation rate explains between 28 and 40 per cent of unemployment variability and between 15 and 32 per cent in the post-1985 period. In addition, Elsby *et al.* (2009) conduct a thorough analysis and show that inflows into unemployment play a noteworthy role in driving unemployment dynamics, namely during recessions.

The renewed interest in the assessment of the importance of job creation and destruction in driving the unemployment rate has also led to a growing body of literature covering countries other than the U.S. In this respect, Petrongolo and Pissarides (2008) study the dynamics of unemployment in three European countries, namely, the United Kingdom, France, and Spain. Smith (2011) also focuses on the UK case, whereas more recently Elsby *et al.* (2013) provide a set of comparable estimates for the rates of inflow to and outflow from unemployment for fourteen OECD economies. They find that fluctuations in both inflow and outflow rates contribute substantially to unemployment variability within countries. Among other findings, they confirm that European labor markets are sclerotic in the sense that they display substantially lower rates of reallocation of labor, as described in Blanchard and Summers (1986) and Blanchard and Portugal (2001).

In this paper we revisit this debate, providing an in-depth assessment of the contribution over time of the incidence and duration of unemployment at different frequencies, relying upon a flexible statistical method – the wavelet analysis – which lends itself to a thorough, but easily interpretable, graphic depiction of the decomposition of the unemployment rate. At high frequencies, i.e. short-run movements, wavelet analysis has a small time support, enabling it to focus on short-lived phenomena, whereas at low frequencies, it has a large time support, allowing it to identify long periodic behavior. By moving from low to high frequencies, wavelet analysis allows us to zoom in on the behavior of a variable at a particular point in time, while it can zoom out to reveal the long and smooth features of a series.

An important advantage of such an approach is that it can accommodate the asymmetry of expansions and recessions. Proceeding in this way, we can take on board the notions that "recessions are much more abrupt than expansions" (Blanchard and Diamond, 1990, p.115) or that "contractions in employment are briefer and more violent than expansions" (McKay and Reis, 2008, p.739). Indeed, resorting to wavelets, we show that the (employment) recessions in the U.S. tend to be short-lived, violent, and heavily influenced by job separations, indicating that the "timing of job destruction is endogenous and concentrated in recessions" (Blanchard and Diamond, 1990, p.114). More generally, our characterization of recessions is consistent with the notion of "intertemporal bunching" which is suggested by the heat wave analogy proposed by Lawrence Summers (heat waves precipitate the death of individuals in frail health) or the pit stop analogy advanced by Valerie Ramey (yellow flags signal slow speed and, thus, time to improve the car).

The paper is organized as follows. In section 2 we lay down the main building blocks of wavelet analysis and propose a wavelet-based decomposition of the unemployment rate variability. In section 3 we review the results obtained with previous approaches and discuss the novel insights drawing on the wavelet-based approach. Section 4 concludes.

2. A wavelet lens

2.1. A primer on wavelets

The well-known Fourier transform is the conventional method for investigating the frequency content of a time series. It involves the projection of a series onto an orthonormal set of trigonometric components (see, for example, Priestley (1981)). In particular, the Fourier transform of the time series $x(t)$ is given by the following convolution

$$F_x(\omega) = \int_{-\infty}^{+\infty} x(t)e^{-i\omega t}dt \tag{1}$$

where ω is the angular frequency and $e^{-i\omega t} = \cos(\omega t) - i\sin(\omega t)$ according to the Euler's formula. Hence, the Fourier transform uses a basis of sines and cosines of different frequencies to determine how much of each frequency the signal contains. However, the Fourier transform does not allow for any time dependence of the signal and therefore cannot provide any information regarding the time evolution of its spectral characteristics. In other words, the analysis is silent about when those frequency components occurred.

To overcome this caveat the short-time Fourier transform has been proposed. It basically consists of applying a short-time window to the signal and performing the Fourier transform within this window as it slides across all the data. The role of the window is to localize the signal in time.

However, the time-frequency analysis is limited by the Heisenberg uncertainty principle. In quantum physics, the uncertainty principle, formulated by Heisenberg, states that the velocity and the position of a moving particle cannot be simultaneously known to arbitrary precision. In the current context, it implies that one cannot know with absolute accuracy what frequency exists at what time instance. The best one can do is to investigate which spectral components exist at any given interval of time. Since the resolution in time and frequency cannot be arbitrarily small, because their product is lower bounded, the researcher always faces a trade-off between time and frequency resolution. This means that for narrow windows one obtains good time resolution but poor frequency resolution, whereas for wide windows one obtains good frequency resolution and poor time resolution.

The problem with the short-time Fourier transform is that it applies constant length windows. When a wide range of frequencies is involved, the fixed time window tends to contain a large number of high frequency cycles and a small number of low frequency cycles, which results in an over-representation of high frequency components and an under-representation of the low frequency components. Hence, as the signal is examined under a fixed time-frequency window with constant intervals in the time and frequency domains, the short-time Fourier transform does not allow an adequate resolution for all frequencies.

In contrast, in the case of the wavelet transform, the time resolution is intrinsically adjusted to the frequency with the window width narrowing when focusing on high frequencies, while widening when assessing low frequencies.

Allowing for windows of different size improves the frequency resolution of the low frequencies and the time resolution of the high frequencies.

In particular, the continuous wavelet transform decomposes a time series in terms of some elementary functions, called daughter wavelets or simply wavelets. The term wavelet means a small wave. The smallness refers to the condition that this function is of finite length, while the wave means that it is oscillatory. These basis functions are obtained by translation and dilation of the mother wavelet $\psi(t)$ in the following way

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{2}$$

where τ is the time position (translation parameter), s is the scale (dilation parameter), which is related with the frequency, and $\frac{1}{\sqrt{s}}$ is a normalization factor. The term translation is related to the location of the window, as the window is shifted through the signal. The scale refers to the width of the wavelet. By changing the scale parameter, one obtains compressed and stretched versions of the mother wavelet. If $s < 1$ then the wavelet is compressed; the wavelet corresponding to $s = 1$ is the mother wavelet; if $s > 1$ then one obtains a stretched version of the mother wavelet. In terms of frequency, low scales by a compressed wavelet function capture rapidly changing details (i.e., high frequencies), whereas higher scales by a stretched wavelet function capture slowly changing features (i.e., low frequencies).

The continuous wavelet transform of a time series $x(t)$ with respect to $\psi(t)$ is given by the following convolution

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\psi^*_{\tau,s}(t)dt \tag{3}$$

where * denotes the complex conjugate. Following the seminal work by Torrence and Compo (1998), for a discrete time series $x(n)$, $n = 0, ..., N-1$, of time step δt, we have

$$W_x(n, s) = \sum_{n'=0}^{N-1} x(n')\sqrt{\frac{\delta t}{s}}\psi^*\left(\frac{(n'-n)\,\delta t}{s}\right). \tag{4}$$

In essence, we are computing a convolution of the signal with the scaled wavelet.[1]

The most commonly used mother wavelet for the continuous wavelet transform is the Morlet wavelet, which can be simply defined as

$$\psi(\eta) = \pi^{-\frac{1}{4}} e^{i\omega_0 \eta} e^{\frac{-\eta^2}{2}} \tag{5}$$

One can see that the Morlet wavelet is a complex sine wave within a Gaussian (bell-shaped) envelope. The normalization factor, $\pi^{-\frac{1}{4}}$, ensures that the wavelet function has unit energy. The parameter ω_0 is the wavenumber and controls the number of oscillations within the Gaussian envelope.[2]

One important quantity that can be defined in the wavelet domain is the wavelet power spectrum (WPS). The WPS for variable x is given by

$$WPS_x(n,s) = |W_x(n,s)|^2 \tag{6}$$

and it measures the power (or variance) of x at each point in time and scale. By plotting the WPS one is able to identify both time and frequency varying behavior. Consider, for instance, the well-known case of the Great Moderation in the United States, where a declining output volatility has been documented by, for example, McConnell and Pérez-Quirós (2000) and Blanchard and Simon (2001). In this respect, wavelet analysis can be useful not only for identifying time-varying volatility but also for assessing which frequency components (that is, shorter or longer-run movements) were driving such a phenomenon.

Note that one can average WPS_x over a particular time interval, say between observation $n_1$and n_2, and obtain the time-averaged wavelet spectrum

$$\overline{WPS}_x(s) = \frac{1}{n_2 - n_1 + 1} \sum_{n=n_1}^{n_2} |W_x(n,s)|^2 \tag{7}$$

1. Although one can use an arbitrary set of scales, Torrence and Compo (1998) argue that it is convenient to write the scales as fractional powers of two, that is, $s_j = s_0 2^{j\delta j}$, $j = 0, 1, ..., J$ where s_0 is the smallest resolvable scale and J, which determines the largest scale, is defined as $J = \delta j^{-1} \log_2(N\delta t/s_0)$. By using $J+1$ scales we obtain a field $N \times (J+1)$ that represents the time-scale plane.

2. In practice, ω_0 is typically set to 6 as it provides a good balance between time and frequency localization. As the wavelength for the Morlet wavelet is given by $\frac{4\pi s}{\omega_0 + \sqrt{2+\omega_0^2}}$, then for $\omega_0 = 6$, the wavelet scale s is almost identical to the Fourier period.

which measures the variance over that time span. For instance, this result can be used to assess the behavior at time periods of different nature, say recessions and expansions. If $n_1 = 0$ and $n_2 = N - 1$, then one is averaging over the whole sample period, and we obtain the global wavelet spectrum, which is an estimator of the spectrum of a time series. In addition, if one is interested in a certain range of scales, say from scales s_{j_1} up to s_{j_2}, one can resort to the scale-averaged wavelet spectrum defined as

$$\overline{WPS}_x(n) = \frac{\delta_j \delta t}{C_\delta} \sum_{j=j_1}^{j_2} \frac{|W_x(n, s_j)|^2}{s_j} \tag{8}$$

where C_δ is scale independent and is constant for each mother wavelet.[3] The scale-averaged wavelet spectrum measures the variance in a certain frequency range of interest. In this way one obtains a time series of the average variance over that range of scales. This result can be especially useful if one intends to study the fluctuations at a given frequency band over time, say at the business cycle frequency range. Note that if $j_1 = 0$ and $j_2 = J$ then one takes on board all scales, and we obtain a series for the average variance for variable x over time.

Furthermore, given two time series $x(n)$ and $y(n)$, with wavelet transforms $W_x(n, s)$ and $W_y(n, s)$, one can define the cross-wavelet spectrum as

$$W_{xy}(n, s) = W_x(n, s) W_y^*(n, s) \tag{9}$$

As the mother wavelet is in general complex, as is the case of the Morlet wavelet, the cross-wavelet spectrum is also complex valued and it can be decomposed into real and imaginary parts. The real part of the cross-wavelet spectrum, $\Re\left(W_{xy}(n, s)\right)$, measures the contemporaneous covariance in the time-scale space.

In the next section we show how one can take advantage of the above concepts to unveil the contributions of the job finding and separation rates for the behavior of the U.S. unemployment rate in the time-scale space.

3. In particular, $C_\delta = 0.776$ for the Morlet wavelet with $\omega_0 = 6$.

2.2. A wavelet-based decomposition of the unemployment rate

As argued in Shimer (2012), the evolution of the actual U.S. unemployment rate, u_t, can be well approximated by the steady-state unemployment rate, u_t^*, that is

$$u_t \simeq u_t^* = \frac{s_t}{s_t + f_t} \tag{10}$$

where s_t and f_t are the employment exit and job finding rates, respectively. Herein, and as in most literature on unemployment fluctuations, we focus on the transitions between employment and unemployment and do not take into account transitions to or from inactivity, or from job to job. As shown by Shimer (2012) the main findings for the U.S. case do not change when inactivity flows are considered. The same is found by Elsby *et al.* (2013) for a panel of countries.

One of the key issues in the related literature has been on disentangling unemployment fluctuations in the contributions of the job finding and employment exit hazard rates. Shimer (2012) suggests computing the hypothetical unemployment rates

$$u_t^{*,f} = \frac{\overline{s}}{\overline{s} + f_t} \tag{11}$$

and

$$u_t^{*,s} = \frac{s_t}{s_t + \overline{f}} \tag{12}$$

where $\overline{s}$ and $\overline{f}$ denote the historical averages of s_t and f_t. The contribution of the job finding rate (employment exit rate) to unemployment variability is quantified by regressing detrended hypothetical unemployment rate $u_t^{*,f}$ $(u_t^{*,s})$ on detrended u_t^*, where detrending is accomplished through the well-known Hodrick and Prescott (1997) filter with smoothing parameter 10^5. As acknowledged by Shimer (2012), although this is not an exact decomposition, the sum of the contributions is very close to 1.

Alternatively to the above-mentioned counterfactual exercise, Fujita and Ramey (2009) suggest an exact decomposition of unemployment variability by performing a log-linearization of u_t^* through a first-order Taylor approximation around the trend, which yields the following formula

$$\ln\left(\frac{u_t^*}{\overline{u_t^*}}\right) = \left(1 - \overline{u_t^*}\right)\ln\left(\frac{s_t}{\overline{s_t}}\right) - \left(1 - \overline{u_t^*}\right)\ln\left(\frac{f_t}{\overline{f_t}}\right) + \varepsilon_t \tag{13}$$

where $\overline{u_t^*}$, $\overline{s_t}$ and $\overline{f_t}$ are the trend components. This allows us to replace the non-linear relation in (10) by a relation which is linear in the log-deviations of the variables. Recall that the log-deviations are approximately the percentage changes. This strategy allows us to write the deviations of unemployment as the sum of factors that depend separately on the deviations of employment exit and job finding rates, which turns out to be very convenient for disentangling the corresponding contributions, along with a residual term that is typically negligible.

To abbreviate notation, let us rewrite (13) in a more compact form as

$$du_t^* = du_t^{eer} + du_t^{jfr} + \varepsilon_t \tag{14}$$

where $du_t^* = \ln\left(\frac{u_t^*}{\overline{u_t^*}}\right)$, $du_t^{eer} = \left(1 - \overline{u_t^*}\right)\ln\left(\frac{s_t}{\overline{s_t}}\right)$, and $du_t^{jfr} = -\left(1 - \overline{u_t^*}\right)\ln\left(\frac{f_t}{\overline{f_t}}\right)$. As in Fujita and Ramey (2009), a convenient way to decompose unemployment variance is

$$Var\left(du_t^*\right) = Cov\left(du_t^*, du_t^{eer}\right) + Cov\left(du_t^*, du_t^{jfr}\right) + Cov\left(du_t^*, \varepsilon_t\right) \tag{15}$$

with the contribution of the employment exit rate to unemployment variability given by

$$\beta^{eer} = \frac{Cov\left(du_t^*, du_t^{eer}\right)}{Var\left(du_t^*\right)} \tag{16}$$

and the contribution of the job finding rate to unemployment variability as

$$\beta^{jfr} = \frac{Cov\left(du_t^*, du_t^{jfr}\right)}{Var\left(du_t^*\right)} \tag{17}$$

Fujita and Ramey (2009) consider deviations from a trend extracted with the HP filter with smoothing parameter 1600 as well as deviations from the previous observation, which corresponds to the first difference filter (see also Petrongolo and Pissarides (2008) and Elsby *et al.* (2013)). One should note that the decomposition approaches by Shimer (2012) and Fujita and Ramey (2009) yield empirically similar figures in the case of log-detrending with the same filtering procedure but the results seem to be sensitive to the detrending method, as shown in the next section.

Hence, we do not pursue any of those filtering alternatives as they can affect the frequency content of the decomposition. Instead, we adopt the decomposition in (13) and set the trends as constant and equal to the corresponding historical averages, in the spirit of Shimer (2012). Then, by taking on board the wavelet counterparts for the covariance and variance as discussed earlier, one can define the corresponding contributions to unemployment variability in the time-scale space as

$$\beta^{eer}(n,s) = \frac{\Re\left(W_{du_t^*,du_t^{eer}}(n,s)\right)}{\left|W_{du_t^*}(n,s)\right|^2} \tag{18}$$

$$\beta^{jfr}(n,s) = \frac{\Re\left(W_{du_t^*,du_t^{jfr}}(n,s)\right)}{\left|W_{du_t^*}(n,s)\right|^2} \tag{19}$$

Such wavelet based measures allow one to assess the contributions to unemployment variability over time and across frequencies within a unified framework.[4] In particular, this novel approach enables us to unveil time- and frequency-varying features of the contributions of the job finding and employment exit rates to the U.S. unemployment behavior.

3. Decomposition results

3.1. Previous approaches

Regarding the data, we consider an updated version of the data used in Shimer (2012).[5] The job finding and employment exit rates are obtained as described in Shimer (2012) and the sample runs from the first quarter of 1948 up to the first quarter of 2015, encompassing 269 quarterly observations.

First, we compute the contributions of the job finding and employment exit rates to U.S. unemployment variability using both the counterfactual exercise of Shimer (2012) and the exact decomposition of Fujita and Ramey (2009). For both methods we consider the first difference filter and the HP filter

4. Note that a naïve approach to obtain a time-varying measure of each contribution would be through the computation of (16) and (17) by considering a rolling window sample. However, besides the subjectivity associated with the issue of setting the window size which, of course, affects the results, one would not be able to disentangle the role played by movements of different frequency.

5. Robert Shimer kindly provided us with an updated version of the publicly available dataset at https://sites.google.com/site/robertshimer/research/flows.

with the two above-mentioned smoothing parameters, namely 1600 and 10^5, with the variables in logarithms. Finally, we also assess the cases in which no detrending is performed for the counterfactual exercise and the historical average is considered for the trend in the exact decomposition. The results are shown in Table 1.

	β^{eer}	β^{jfr}
Counterfactual		
First difference filter	0.37	0.63
HP filter with smoothing parameter 1600	0.28	0.72
HP filter with smoothing parameter 10^5	0.24	0.75
No detrending	0.21	0.78
Exact decomposition		
First difference filter	0.37	0.63
HP filter with smoothing parameter 1600	0.28	0.71
HP filter with smoothing parameter 10^5	0.24	0.76
Historical average	0.21	0.78

TABLE 1. Decomposition of the unemployment rate variability

Note: β^{eer} and β^{jfr} stand for the contribution of employment exit and job finding rates to unemployment rate variability, respectively.

Several remarks arise with the results in Table 1. Based on the HP filter with smoothing parameter 10^5, the job finding rate accounts for around three quarters of the U.S. unemployment variability, while the employment exit rate accounts for the remaining quarter. This corresponds to the main quantitative finding reported by Shimer (2012). Resorting to the HP filter with smoothing parameter 1600 and the first-difference filter, we obtain 0.28 and 0.37, respectively, for the contribution of the employment exit rate, which are very close to the results reported by Fujita and Ramey (2009). In this respect, as mentioned previously, the results obtained with the counterfactual exercise and the exact decomposition are essentially the same as long as the same filtering procedure is adopted (see also Hairault *et al.* (2015)). One should also note that using the historical average for the exact decomposition corresponds to the no detrending case in the counterfactual exercise. This reinforces the idea that the frequency content is not being changed by using the historical average in the exact decomposition, as expected.

However, the results vary depending on the detrending procedure. We find that the more one reduces (increases) the relative importance of the low frequencies (high frequencies), the higher is the contribution of the employment exit rate for unemployment variability. In fact, in the cases of no detrending in the counterfactual exercise and the use of historical averages in the exact decomposition, which are the ones that do not remove any low frequency component, we obtain the lowest contributions of the employment exit rate.

Regarding the HP filter, it acts like a high-pass filter with the smooothing parameter influencing the cut-off frequency (see King and Rebelo (1993)). The choice of a smoothing parameter of 1600, which is typically the value used with quarterly data, implies that only fluctuations shorter than eight years are retained in the detrended series (see Baxter and King (1999)). The higher is the smoothing parameter the lower is the implicit cut-off frequency, meaning that the trend component retains lower frequencies. This is what underlies Shimer's (2012) reasoning when he states that the HP filter with the standard smoothing parameter removes much of the cyclical volatility of the variable of interest and prefers using a much lower-frequency filter using a higher smoothing parameter, namely 10^5.

Concerning the first-difference filter, it involves a substantial reweighting of the frequency components. In particular, it emphasizes the higher frequencies while downweighting the lower frequencies as the gain function of this filter increases with frequency (see Baxter and King (1999)). This filter, which overweights high frequencies, is the one that delivers a higher contribution of the employment exit rate. So what these results seem to suggest is that the contribution of the employment exit rate is not the same across all frequencies and, in particular, is higher at high frequencies. In this respect, Elsby *et al.* (2013) also argue that using annual data may implicitly lead to some smoothing out of high-frequency variation, which likely results in an understatement of the contribution of the inflow rate to unemployment variability.

The fact that the detrending method influences the results seems to suggest that the frequency level matters. In other words, if the contributions were constant across frequencies, then one would not expect the results to change, regardless of the frequency range one is focusing on through the filtering procedure. Furthermore, it is plausible to argue that such contributions depend on the stage of the economic cycle, as discussed by Elsby *et al.* (2009), and therefore the time dimension cannot be discarded. Given such a background, the potential usefulness of the wavelet analysis to unveil such features becomes clear. Hence, we now proceed with the wavelet-based analysis of the contributions of the job finding and employment exit rates for the U.S. unemployment variability.

3.2. The wavelet-based approach

In Figures 1 and 2 we plot the contributions to unemployment variability computed following (18) and (19), respectively. The results are displayed in a 3-D surface plot, as there are three dimensions involved. The x-axis refers to time and the y -axis to scale. For easier reading, the scale is converted to time periods, namely years. The height of the surface represented by the z-axis corresponds to the value of the contribution to unemployment variability at around each moment in time and scale. As the continuous wavelet transform at a given point in time uses information of neighboring data points, the values of the wavelet transform are generally less accurate as the wavelet approaches the edges of the time-series. This region is known as the cone of influence (see Torrence and Compo (1998)).[6] The results inside the cone of influence are displayed in white and should not be over-interpreted. In addition, to better distinguish recessionary from expansionary periods, we display as black shaded areas the recessions as defined by the NBER Business Cycle Dating Committee.

6. With finite length time-series, edge effects occur at the beginning and end of the sample period. Moreover, the region affected increases with the temporal support (or width) of the wavelet, that is, the region affected is larger for lower frequencies. Hence, as is usual in this type of analysis, we restrict the figures to the lowest frequency (i.e. maximum scale) where there is at least some part outside the cone of influence.

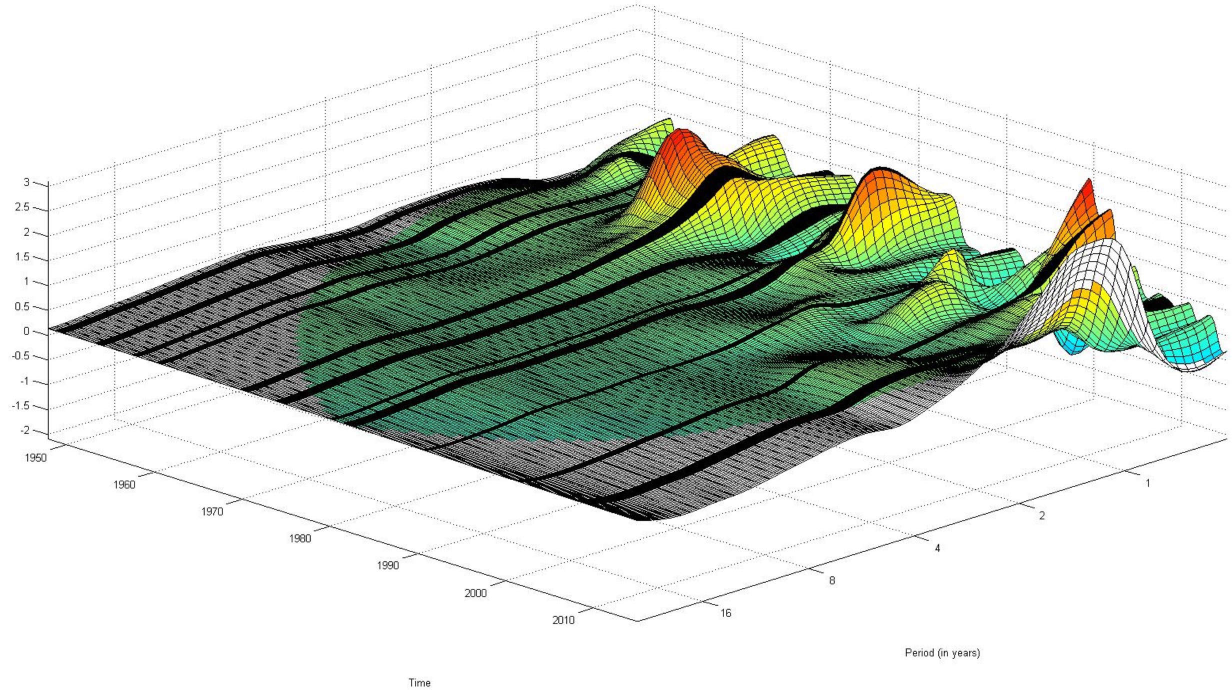

FIGURE 1: Contribution of the employment exit rate to unemployment variability

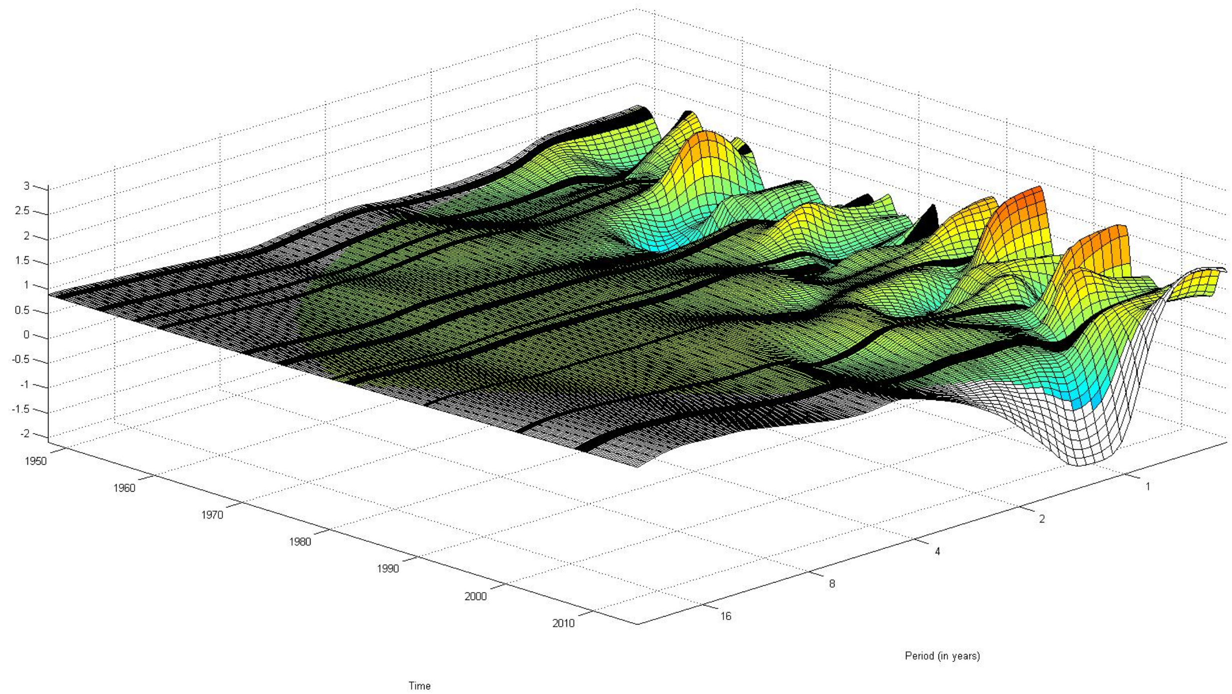

FIGURE 2: Contribution of the job finding rate to unemployment variability

From Figures 1 and 2 it becomes clear that, underlying a single value in Table 1, namely a contribution of 0.21 for the employment exit rate and 0.78 for the job finding rate, there is a striking heterogeneity over time and across frequencies. This clearly highlights that both dimensions should be taken into account in the analysis.

Focusing on Figure 1, one can see that the contribution of the employment exit rate for the unemployment rate is much more stable over time for movements that last more than say two years than for shorter-run fluctuations. In the former case, the contribution stands at around 0.2. In contrast, for short-run fluctuations the contribution changes substantially over time. In this respect, the contribution is particularly high during the recessionary periods of the late 1960s, early 1980s, and beginning of 2000s.

Bearing in mind that both contributions sum to approximately one at each point in time and scale, Figure 2 is the mirror of Figure 1. In fact, the contribution of the job finding rate is also relatively stable for fluctuations that last more than two years. In this case, the contribution is around 0.8. Furthermore, one can see that the contribution of the job finding rate also reveals a noteworthy time variation at short-run fluctuations being higher during expansions than in recessions, namely since the 1980s.

To reinforce and to guide through the findings that emerge from Figures 1 and 2, it can be useful to collapse the time and frequency dimensions separately. Analogously to (7) and (8), we can compute the time- and scale-averaged measures of the contributions of the employment exit and job finding rates to U.S. unemployment variability.

In Figure 3 we plot the time-averaged contributions, that is, we integrate over time and retain the frequency dimension. Figure 3 highlights that contributions of employment exit and job finding rates vary considerably with frequency. In particular, the contribution of employment exit rate broadly decreases with the frequency, meaning that it is more important for determining short-run fluctuations of unemployment rate than for long-term movements. Again, as the contributions basically sum up to one, the opposite holds true for the job finding rate. Such a finding explains why the contribution of the employment exit rate decreases when one takes on board longer-term movements by using a lower frequency filter, as discussed earlier. For high frequencies, the contribution is near 0.5, while decreasing steadily for lower frequencies. Such evidence clearly supports the finding that the employment exit rate plays a noteworthy role, namely for short-run fluctuations of the U.S.

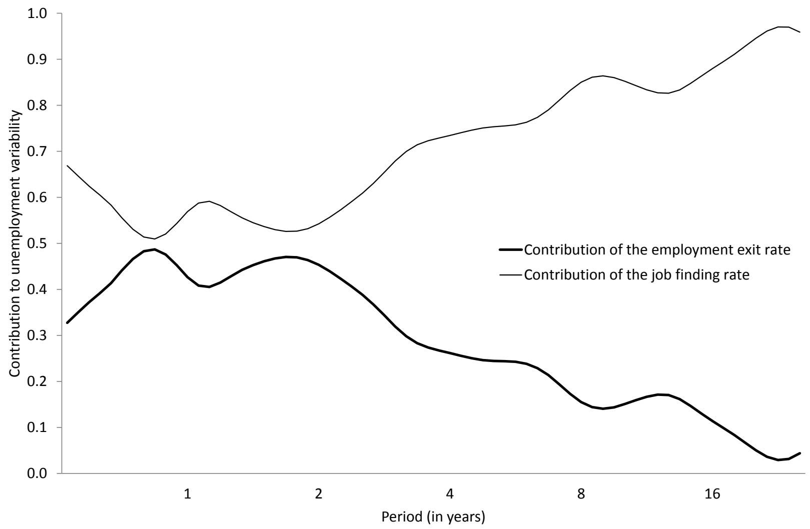

FIGURE 3: The time-averaged contributions to unemployment variability

unemployment rate whereas for long-term movements the unemployment rate is essentially driven by the job finding rate.

In Figure 4 depicts the scale-averaged contributions, that is, we now integrate over all scales and allow only for time-varying features. A decreasing (increasing) trend over time of the contribution of the employment exit rate (job finding rate) to unemployment variability becomes clear. This is in line with the results reported by Shimer (2012) and Fujita and Ramey (2009).

However, the conclusions drawn from Figures 3 and 4 are not the end of the story, as we already know from Figures 1 and 2 that there is a substantial heterogeneity in the time-scale space. Although Figure 3 allows us to conclude that the employment exit rate is more important for shorter-run fluctuations of the unemployment rate, we also know that this contribution has changed considerably at those frequencies over time.

Given the findings described above, we complement the above analysis, proceeding in the following way. Let us narrow the frequency dimension by considering three frequency bands. As is standard in the business cycle literature, we will consider the typical business cycle frequency range

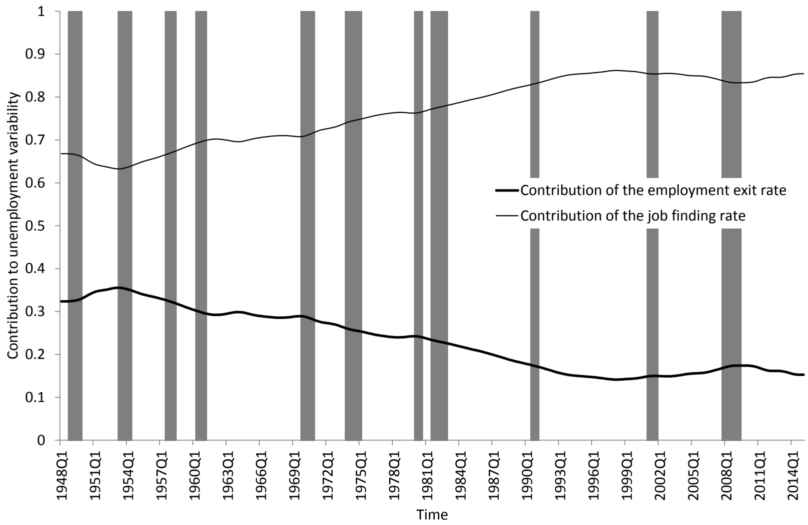

Figure 4: The scale-averaged contributions to unemployment variability

encompassing cycles of periodicity between 6 and 32 quarters. One should note that this is the standard frequency range considered for band-pass filtering when extracting the U.S. business cycle. Nevertheless, as stressed by McKay and Reis (2006), this does not mean that it is the most relevant definition when focusing on the labor market. Thus, to avoid any misreading, we will use the term medium-run frequency range instead of business cycle. As a result, the high frequency band includes all fluctuations that last fewer than 6 quarters, whereas the low frequency range reflects movements longer than 8 years.

Hence, we now compute the scale-averaged contributions corresponding to each of the frequency bands and plot them against time (Figures 5 and 6). As expected, the contributions at the high frequency band display much more time variation than at the remaining frequencies. Concerning long-term movements in the unemployment rate, we find a slowly declining trend in the contribution of the employment exit rate, from around 0.3 at the beginning of the sample to 0.1 in the most recent period. Naturally, in the case of the job finding rate, it goes from 0.7 to 0.9 in the latest years. At the medium-run frequency range, the contribution of the employment exit rate was near 0.35

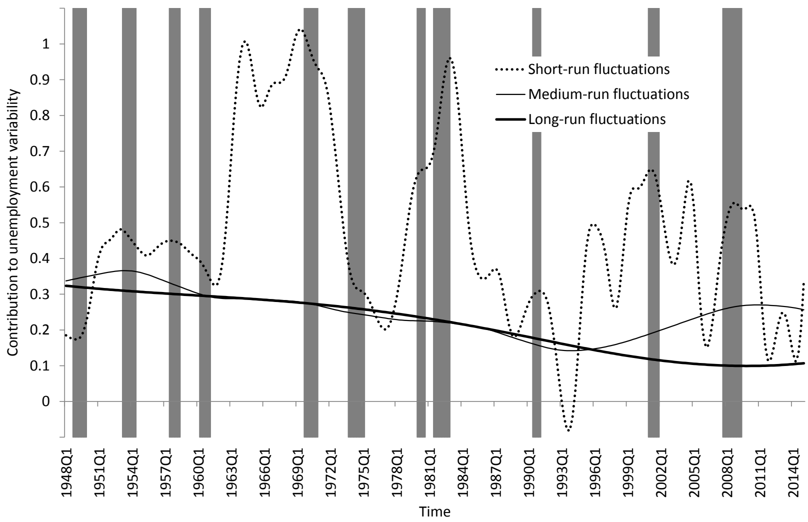

Figure 5: The contribution of the employment exit rate by frequency band

at the beginning of the 1950s and then decreased until the mid-90s attaining a value of around 0.15 increasing thereafter to around 0.25. Again, the evolution of the contribution of the job finding rate mirrors the one of the employment exit rate. Regarding the contribution of the employment exit rate to short-run fluctuations in the unemploymnent rate, from Figure 5 one can see that it tends to increase before recessions, attaining most of the time a local maximum during the contractionay periods. Moreover, the size of the contribution is in general quite substantial during contractions, although its magnitude varies from recession to recession. To summarize this evidence, we present in Table 2 the contribution of the employment exit rate at the different recessionary periods and frequency bands by time- and scale-averaging the corresponding regions in Figure 1.

When all fluctuations are taken on board, the employment exit rate accounts for, on average, around one quarter of the unemployment rate variability during recessions. Moreover, its contribution shows a downward trend throughout time, in line with the evidence reported in Figure 4. However, we find that the contribution of the employment exit rate to the short-run fluctuations of

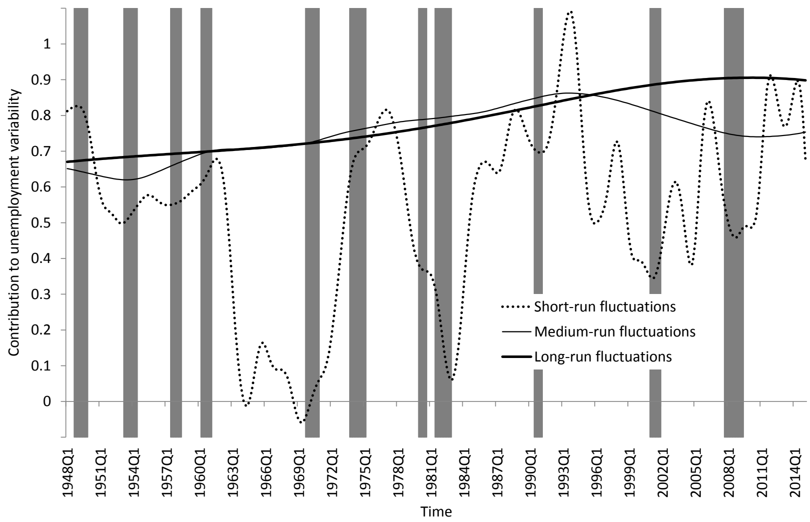

Figure 6: The contribution of the job finding rate by frequency band

	Frequency range			
	All	Short-run	Medium-run	Long-run
All recessions	0.26	0.53	0.27	0.23
1948Q4-1949Q4	0.33	0.19	0.35	0.32
1953Q2-1954Q2	0.35	0.46	0.37	0.31
1957Q3-1958Q2	0.32	0.45	0.33	0.30
1960Q2-1961Q1	0.30	0.37	0.30	0.30
1969Q4-1970Q4	0.29	0.98	0.27	0.27
1973Q4-1975Q1	0.26	0.33	0.25	0.26
1980Q1-1980Q3	0.24	0.65	0.23	0.24
1981Q3-1982Q4	0.23	0.85	0.22	0.23
1990Q3-1991Q1	0.17	0.31	0.16	0.18
2001Q1-2001Q4	0.15	0.63	0.19	0.12
2007Q4-2009Q2	0.17	0.53	0.26	0.10

Table 2. Contribution of the employment exit rate for unemployment variability during recessions

the unemployment rate during recessions is greater than one half and therefore higher than that of the job finding rate. Such a contribution ranges from 0.19

in the late 1940s recession and almost one during the contraction of 1969Q4-1970Q4, with most of the recessionary episodes displaying a sizeable magnitude. Note that even during the last two recessions, the contribution for short-run fluctuations is greater than one half. Hence, the above mentioned downward trend is essentially reflecting the decrease of its contribution for long-term movements and to a lesser extent, for medium-run fluctuations. For the short-term fluctuations of the unemployment rate, the employment exit rate continues to be quite important and its relevance has not decreased over time. Such wavelet-based evidence clearly supports the idea that the employment exit rate plays, and continues to play, an important role in driving the unemployment rate during contractions.[7]

The reasoning behind the finding that such an important role during recessions becomes overwhelming only when one focuses on short-run fluctuations, may reflect the fact that recessions are typically short-lived movements. According to the NBER, since 1948 recessions have lasted, on average, around 11 months with a duration ranging from 6 to 18 months. Moreover, recessionary periods are also characterized by abrupt changes in the labor market that end up being captured at the high frequency band. In this respect, when studying the brevity and violence of employment contractions, McKay and Reis (2006) report that the evidence in favor of the violence of employment contractions increases if one removes only very low frequencies instead of focusing on fluctuations in the range of 6 to 32 quarters.[8] Furthermore, since the effects of the inflow rate tend to be stronger at recessions, namely at the beginning, as pointed out by Elsby *et al.* (2009) (see also Barnichon (2012)), then it is natural that a higher contribution of the employment exit rate shows up at the high frequency range during recessions.

Hence, the above wavelet-based analysis allows us to conclude that the employment exit rate is not irrelevant. However, such a statement needs a proper qualification. We find that in line with Shimer's (2012) evidence, the

7. As a sensitivity analysis we also assessed the corresponding contributions using the dating procedure suggested by Elsby *et al.* (2009). Start dates are determined by the most recent minimum quarterly unemployment rate preceding each NBER recession start date while the end dates are established based on the highest quarterly unemployment rate following each NBER recession end date. We find that the results are quite similar.

8. McKay and Reis (2006) consider a filter to extract the fluctuations between 2 and 80 quarters, which they argue that removes only the very low frequency movements of unemployment that are associated with demographic changes.

job finding rate is the main driver for medium to long-run movements in the unemployment rate and that this role has increased over time. However, we also find that the employment exit rate plays a key role in determining short-run fluctuations in the unemployment rate namely during recessions. Note that this also holds true in the latest recessionary periods, including the Great Recession. In this sense, such novel findings support the view originally advocated by Darby et al. (1986), Blanchard and Diamond (1989, 1990), among others, that the employment exit rate matters, and continues to matter, for unemployment variability.

4. Concluding remarks

In this paper we employed a novel technique to disentangle the way that separation and job finding probabilities drive unemployment rates in the U.S. The wavelet analysis is flexible and general, avoiding the need to make any decision about detrending or smoothing the original data. In essence, the wavelet approach represents, in a thoroughly convenient way, the evolution of the series at the time and frequency domains simultaneously. Within this non-parametric framework, we were able to measure the influence of job separation and job finding rates on unemployment rates over the time-frequency space.

Overall, the U.S. unemployment rate is more heavily affected by the variability of the job finding rate (or, conversely, the mean duration unemployment). In our setting the job finding probability accounts for 78 percent of the variability of the unemployment rate. This is because the impact of job finding probability has been trending up over the last decades and because it is more influential at lower frequencies, especially the ones that macroeconomists associate with cyclical frequencies. This outcome largely vindicates the assertion of Robert Shimer when he claims that "job finding probability explains three-quarters of the volatility in the unemployment rate" (Shimer, 2012, p.147).

Having said that, the job separation rate also plays an important role, especially during recessions. Indeed, at relatively high frequencies, the job separation rate is more influential than job finding probability shaping the evolution of unemployment rates during recessions. At short-run movements during recessions, the job separation probability contributes, on average, 53 percent (between 19 percent in the 1948/49 recession and 85 percent during the 1981/82 recession) to the variability of the unemployment rate. This result supports the notion that the job separation probability is critically important during recessions, when decisions to displace workers tend to be clustered at (short) particular times (Blanchard and Diamond, 1990; Elsby *et al.*, 2009; McKay and Reis, 2008).

The asymmetry of the roles of job finding and job separation rates in recessions and expansions raises some issues regarding the adequacy of the ingredients used to model the cyclical behavior of unemployment. What we observe in the data calls not only for asymmetric labor adjustment cost between hiring and firing (as in McKay and Reis, 2008), but alerts us to significant non-convexities associated with costs of displacement. Lumpy, short-lived, violent employment contractions are the expected consequences of a labor market characterized by (large) fixed firing costs (Caballero and Hammour, 1996). The non-convexity of firing costs may, indeed, attenuate the cyclicality of job separation rate, generating brief and violent employment contractions. This does not, of course, preempt the role of job separations timing and shaping the cyclical behavior of unemployment.

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