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The cyclicality of the separation and job finding rates in France

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ABSTRACT

In this paper, we shed light on the relative contribution of the separation and job finding rates to French unemployment at business cycle frequencies by using administrative data on registered unemployment and labor force surveys. We first investigate the fluctuations in steady state unemployment, and then in current unemployment in order to take into account the unemployment deviations from equilibrium. Both data sets lead to quite similar results. Both rates contributed to unemployment fluctuations during the nineties (50:50 split), while in the last decade the job finding rate was more significant and explained around 65% of the French unemployment fluctuations. In particular, the last business cycle episode, including the last recession, exacerbated the role of the job finding rate. We then show that the predominant role of the job finding rate in the last decade holds when the economy is hit by aggregate business cycle shocks, moving unemployment and vacancies along the Beveridge curve.

1. Introduction

The analysis of unemployment dynamics between outflows and inflows has recently received a lot of attention. Using CPS data, Shimer (2012) claims that, since 1948, inflows into unemployment have played a minor role in accounting for unemployment dynamics in the US, compared to outflows from unemployment.[1] This conclusion for the US economy has been challenged by Fujita and Ramey (2009) and Elsby et al. (2009) who show that inflows to unemployment quantitatively matter. This conclusion also applies to UK unemployment, according to Petrongolo and Pissarides (2008), Smith (2011) and Gomes (2012). Pissarides (2009) reconciles these diverging views: “A consensus estimate in the literature for the contribution of the inflow rate lies between one-third and one-half of the total” (pp. 1344).

This paper identifies the driving forces behind unemployment dynamics in France. As pointed out by Elsby et al. (2013), this country is particularly interesting because it is often thought to represent a polar case due to its combination of practices and regulations. It exemplifies the polar case of a rigid labor market with strict employment protection laws (Allard, 2005) and low rates of labor reallocation (Blanchard and Portugal, 2001). As suggested by Petrongolo and Pissarides (2008), due to stricter employment protection, a low contribution of the separation rate is expected on French data,

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[1] Since 1948, Shimer (2012) finds that “the job finding probability has accounted for three-quarters of the fluctuations in the unemployment rate in the United States and the employment exit probability for one-quarter”. Furthermore, Shimer (2012) claims that “fluctuations in the employment exit probability are quantitatively irrelevant during the last two decades.”.

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although Elsby et al. (2013) show that the theoretical predictions of employment protection using a canonical search and matching model are not as clear cut as expected.

Two previous papers have already documented the cyclicality of the labor market transitions in France. Firstly, Petrongolo and Pissarides (2008) investigate the contribution of entry and exit rates to and from French unemployment to unemployment fluctuations, using a monthly administrative dataset based on unemployment registers between 1991 and 2007. They find that the relative contribution of the outflow rate from unemployment is dominant (80%). Secondly, Elsby et al. (2013) analyze unemployment dynamics using aggregate annual data on short-term unemployment based on French Labor Force Surveys (hereafter LFS) between 1975 and 2009. They find a 50:50 inflow/outflow split.[2] These quite opposing results could be due to different datasets. Moreover, as far as data are concerned, each paper suffers from some limits, which could bias their conclusion. In this paper, we shed light on the relative contribution of the transition rates to French unemployment at business cycle frequencies by using datasets more in line with international standards.

Petrongolo and Pissarides (2008) use administrative data based on unemployment registers (Statististiques Mensuelles sur le Marché du Travail, hereafter named STMT). The STMT, which is an aggregate count, suffers from several problems. First, some people continue to work while being registered in the Public Employment Service (PES). These workers are counted in the unemployment total, representing roughly 30%. This leads to counting some artificial outflows (when these workers leave the registers) and misses some real inflows of the workers already registered with the PES. This is problematic, as these artificial and real flows are important and cyclical (Abdouni et al., 2011). Secondly, administrative rules (such as reporting at the end of each month) generate spurious transitions in the STMT. The unemployed who do not report their situation in due time are deregistered. They can register again after a few days, so this generates high frequency movements, which do not represent real labor transitions. Thirdly, changes in unemployment legislation (such as eligibility for unemployment benefits and activation schemes) have direct, even mechanical, impacts on inflows and outflows in the STMT. This is problematic as these legal changes are not necessarily related to business conditions. Fourthly, in the STMT, it is not possible to control consistently for the origin of inflows and the destination of outflows. So the cyclical analysis captures transitions mixing employment and inactivity, which blurs the interpretation. We therefore use another administrative dataset (Fichier Historique, hereafter FH dataset) which is subject to the third problem, but relieves us from the other three concerns, mainly because it is an individual panel.

In the literature, international evidence on the source of unemployment dynamics relies on Labor Force Surveys or equivalent datasets. Moreover, only LFS, with their detailed information on individual characteristics, can be used in future studies on more disaggregated data (labor market transitions with inactivity or across age groups, gender, industry). Elsby et al. (2013) rely on the Labor Force Surveys of different countries, including France, provided in a standardized way by the OECD, but at the expense of considering annual time series. We extend Elsby et al. (2013) by providing infra-annual labor market transitions, using the retrospective calendar of the French LFS, which is more in line with previous studies on the US and UK economies. Unlike administrative data, the latter dataset is based on subjective reports and on retrospective data, which could be biased by recall errors. This is why in this paper we propose an innovative strategy to correct the survey data for recall errors, which transpires to be important and helpful for a correct evaluation of the relative contribution of labor market transitions to unemployment dynamics.

We then build two datasets covering several recession and expansion episodes, including the last severe recession, using both administrative data and LFS. As mentioned above, each dataset has its pros and cons. In this paper, we are looking for convergent evidence on French unemployment dynamics. As far as administrative data are concerned, it is not possible to measure transitions between employment and inactivity. A comprehensive three-state analysis cannot then be undertaken. This is why Petrongolo and Pissarides (2008) can only provide an analysis of unemployment dynamics between total outflows from and total inflows to unemployment. Elsby et al. (2013), using duration-based flows, face the same constraint. This approach is problematic as job loss is not distinguished from labor force entry and as job finding also captures labor force exit. This could lead to a mis-evaluation of the contributions of job finding and job separation rates to unemployment fluctuations.

In this paper, we adopt another strategy by focusing on transitions between employment and unemployment, i.e. a two-state view of labor market transitions, as in Fujita and Ramey (2009). We can identify on FH administrative data job separation and job finding transitions, and calculate their labor survey counterparts. Though information on transitions between employment and inactivity would be available in LFS data, we prefer to leave aside this information in order to use two different, but comparable, data sources in order to verify the reliability of our results. This is all the more important as there are missing data for LFS dataset between 2002 and 2004. Adopting this two-state view of labor market transitions, we will refer to the separation rate for transitions from employment to unemployment and to the job finding rate for transitions from unemployment to employment. This allows us to precisely measure the relative contributions of well-identified transitions. From Shimer (2012) and Smith (2011), it is well-established that these transitions explain more than two-thirds of the variability of US and UK unemployment, whatever the relative role of the ins and outs. We check that this result is also relevant on French data. When we take into account the flows involving labor force exits and entries, we show that they are quite inessential in the understanding of unemployment volatility in France.

[2] Elsby et al. (2013) find a 20:80 inflow/outflow split of unemployment variation for Anglo-Saxon countries. For Continental European and Nordic countries, a 50:50 split is observed.

We first investigate the analysis of fluctuations in steady state unemployment along the lines of Shimer (2012) and Fujita and Ramey (2009). This analysis strategy is valid as long as the equilibrium unemployment provides a good proxy for actual unemployment. However, both time series can differ substantially, especially in a labor market with low worker flows, which is the case in France. Whereas Petrongolo and Pissarides (2008) deal with this issue by excluding periods with large discrepancies between changes in actual and steady state unemployment, we explicitly consider a dynamic analysis, thereby taking into account the effect of past changes in transition rates on actual unemployment. This is the strategy followed by Smith (2011) and Elsby et al. (2013) who apply a dynamic analysis to UK data and to OECD data respectively. Whatever the strategy, we consider both HP filtering and first-order difference as methods for detrending the data.

Both data sets lead to quite similar results. Both rates contributed to unemployment fluctuations during the nineties (50:50 split), while in the last decade the job finding rate was more significant and explained around 65% of the French unemployment fluctuations. Over the whole sample, the contribution of the finding rate is substantial (60%). In our view, the dominant contribution of the job finding rate is a salient feature of the French labor market. Indeed, since Shimer (2012)'s paper, papers found a sizable contribution of separation rates in unemployment dynamics (between one-third and one-half, Fujita and Ramey (2009) and Elsby et al. (2009) in the US, Smith (2011) and Gomes (2012) in the UK, Silva and Vazquez-Grenno (2013), in Spain). In the range of results found in the literature, France stands out as a country in which job finding influence on unemployment fluctuations is dominant, especially in recent years. This result calls for two comments. First, the greater role of the job finding rate in the last business cycle episodes, including the last recession, seems consistent with the recent rise of short-term contracts that cannot be broken before their term. We then show that the short-term contracts do give much more importance to the job finding fluctuations. The particular labor market regulations could be part of the influence of the job finding rate in France. Secondly, the dynamic decomposition sheds light on the reason behind this striking feature. In the US, Fujita and Ramey (2009) find that the job separation rate is strongly negatively correlated with future changes in unemployment, which is not the case of the job finding rate. Taking into account this dynamic interaction between transition rates substantially increases the importance of the separation rate in explaining US unemployment variability. In contrast, we find no evidence of such dynamic asymmetries across transition rates in France. The dynamic decomposition therefore confirms the predominant role of the job finding rate. Unlike its US counterpart, the French separation rate does not lead either unemployment or the job finding rate. This is actually a key feature of the French labor market. French data then give a relatively high importance to the job finding rate, even when considering the dynamic decomposition.

We then investigate further the reasons behind the dynamic relationships between rates and unemployment fluctuations. Is this due to the existence of specific shocks relying more on the job finding channel or to particular propagation mechanisms for quite standard business cycle shocks? We therefore propose to identify the relative contribution of the finding and separation rates conditional on well-identified shocks. This is a more structural approach than the traditional unconditional analysis, which could deliver additional insight into the French labor market, especially on the dynamic pattern of the transition rate. Fujita (2011) and Canova et al. (2012) investigate the relative contribution of the finding and separation rates to the US unemployment volatility generated by the aggregate productivity shock present in any quantitative matching models. In order to be comparable with the US economy, we adopt exactly the same methodology as in Fujita (2011). We estimate a parsimonious VAR model including our two computed transition rates in addition to vacancies, in order to identify a structural shock shifting the labor market equilibrium along the Beveridge curve, hereafter named the aggregate shock. We then show that the French economy seems to be characterized by the predominant influence of the job finding rate when the economy is hit by this type of shock, consistent with the results obtained on the basis of unconditional volatility. This means that this influence is mainly due to the adjustment of the French labor market to traditional business cycle shocks, which seems close to the results obtained by Fujita (2011) on US data. However, investigating the impulse response functions confirms that the French dynamic pattern for the transition rates is quite specific: the separation rate is less responsive to the shock and the job finding rate response is not delayed and hump-shaped as in the US, besides the relative importance of the job finding rate in unemployment fluctuations.

The paper is organized as follows. In Section 2, we present the administrative and LFS data, the methodology and the computation behind the French transition rates involving employment and unemployment. In the next section we then compute the relative contribution of separation and finding rates to changes in both equilibrium and actual unemployment. Section 4 analyzes the labor market flow dynamics conditional on a well-identified business cycle shock. The final section concludes.

2. Transitions between employment and unemployment

Along the lines of Petrongolo and Pissarides (2008) and Elsby et al. (2013), both administrative data and individual record files from the LFS are used to analyze the contribution of separation and job finding changes to the dynamics of French unemployment.

2.1. Data

2.1.1. Administrative data

We rely on administrative data produced by the French Public Employment Service. The administrative data (Fichier Historique, FH) is an individual panel, available on a monthly basis from 1994 onwards. It allows us to check whether registered unemployed workers are actually working and to track their transitions in/out of employment even if they stay registered.[3] This information gives a crucial advantage to the FH data compared to the STMT administrative data used by Petrongolo and Pissarides (2008). We then provide a more accurate picture of unemployment dynamics (employment-unemployment transitions). In addition, the FH data give some information about the labor status (employed or not) prior to registering with the agency and after exiting the register. This allows us to measure transitions between employment and unemployment states, and not the ins and outs of unemployment, which put together transitions from and to employment and inactivity.

2.1.2. Labor force survey

As it is of potential interest to also provide a dataset in which information on individual characteristics is available, we then compute worker flows using the LFS. We use the LFS from 1991 through 2010.[4] The survey was redesigned in 2003. Prior to 2003, individuals were surveyed each year, three years in a row. After 2003, each individual is surveyed every quarter, six quarters in a row. The redesign implied huge changes in the process of the survey, which resulted in data problems for the first two years after the redesign.[5] As a result, we chose to drop the data from 2003 and 2004. Our LFS sample covers the periods 1990–2002 and 2004–2010. Our estimates of monthly labor market transitions are based on a retrospective calendar that is filled in by the individual the first time he is interviewed.[6] He reports his labor status one month prior to the interview, two months prior, and so on up to 12 months prior to the interview. Several studies have shown that retrospective data are biased by recall errors. We propose in Section 2.3 an intuitive and innovative strategy to deal with this problem.

2.2. Measuring instantaneous transition rates

To construct the series of worker flows, we refer to the theoretical framework used by Fujita and Ramey (2009) for analyzing the US employment-unemployment flows, and first proposed by Shimer (2012). This framework rests on two assumptions. First, we do not take into consideration transitions to or from inactivity[7], or transitions from job to job. Our analysis focuses on monthly transitions from employment to unemployment and unemployment to employment. Moreover, we assume that during a given period, all the unemployed have the same opportunity to return to work and all employees the same risk of losing their job. Taking into account the heterogeneity of workers that influences the losses and reversals of employment is beyond the scope of our study.

As in Shimer (2012), time is continuous, but the labor market status is observable only in a discrete manner, at the end of every month. LFS and administrative data give the opportunity to measure the probability of returning to work and the probability of job loss over a given month. Nevertheless, these probabilities may underestimate the magnitude of labor flows, to the extent that several transitions to and from employment may be reversed within the period. We follow the method proposed by Shimer (2012) to correct this temporal aggregation bias on both datasets FH and LFS. We adopt the same notations as Shimer (2012) with λ_t^{UE} the instantaneous probability of finding a job (finding rate) and λ_t^{EU} the instantaneous probability of losing a job (separation rate). Let $e_{t+\tau}$ denote the number of employed workers at date $t+\tau$, $u_{t+\tau}$ the number of unemployed workers at the same date $t+\tau$. For $t \in \{0,1,2,\dots\}$ and $\tau \in [0,1]$, the dynamics of unemployed workers are given by the following law of motion:

$$\dot{u}_{t+\tau} = e_{t+\tau}\lambda_t^{EU} - u_{t+\tau}\lambda_t^{UE} \tag{1}$$

Note that both instantaneous rates are considered constant between date t and $t+1$ (over the month). The corresponding transition probabilities Λ_t^{AB} of at least a transition during period t are $\Lambda_t^{AB} \equiv 1 - e^{-\lambda_t^{AB}}$ with $A = \{E,U\}$, $B = \{E,U\}$ and $A \neq B$.

To calculate these transition rates, we first consider the flow N_t^{AB} of workers that are in state A at time t and in state B at time $t+1$. Following the terminology used by Shimer (2012), we will refer to these numbers as gross flows. Let n_t^{EU} (n_t^{UE}) denote the share of employed workers (unemployed workers) in period t who are unemployed (employed) in period $t+1$:

$$n_t^{EU} = \frac{N_t^{EU}}{E_t} \tag{2}$$

$$n_t^{UE} = \frac{N_t^{UE}}{U_t} \tag{3}$$

where E_t and U_t indicate the measured stocks of employed and unemployed workers, respectively. The instantaneous transition rates λ_t^{EU} and λ_t^{UE} will then satisfy[8]:

[3] In France, the unemployment registers are more than just an unemployment benefit claimants count. Around half of registered individuals do not claim any unemployment benefits. See Appendix A for further details on the dataset.

[4] LFS collects data since 1950, but information on monthly transitions have been collected since 1991.

[5] In 2003–2004, the restrospective calendar was erroneously filtered for individuals who were employed since the beginning of the calendar year. This error was corrected afterwards.

[6] Using the retrospective calendar in the LFS 1991 and 2005, we can retrieve monthly data on labor market transitions in 1990 and 2004.

[7] For the sake of robustness, we relax this assumption in Appendix E.

[8] See Footnote 8 in Shimer (2007).

$$n_t^{EU} = \lambda_t^{EU} \left(\frac{1 - e^{-\lambda_t^{EU} - \lambda_t^{UE}}}{\lambda_t^{EU} + \lambda_t^{UE}} \right) \tag{4}$$

$$n_t^{UE} = \lambda_t^{UE} \left(\frac{1 - e^{-\lambda_t^{EU} - \lambda_t^{UE}}}{\lambda_t^{EU} + \lambda_t^{UE}} \right) \tag{5}$$

2.3. Correcting for recall errors

One important drawback of survey data is measurement error. In particular, in the case of labor market surveys, individuals may find it difficult to recognize themselves as being in one labor market status rather than in another (typically between unemployment and out of the labor force) and/or to recall past status. The first difficulty leads to classification error and the second one to recall error. Empirically, the extent of classification and recall errors in labor market transition data can be documented by comparing survey responses with external sources such as administrative data, or comparing responses on the labor status prevailing at one particular date but reported in different interviews. In the case of the US, Horvath (1982) compares monthly responses to CPS interviews with retrospective information derived from its March supplement and shows that recall errors bias aggregate unemployment downwards. Akerlof and Yellen (1985) and Levine (1993) use the same data and show that unemployment is more understated among individuals with weak attachment to the labor market, when unemployment is less salient or when unemployment spells are shorter. Using reinterviews in CPS data, Poterba and Summers (1986) document classification error. Systematic conflicting information depending on the interview date is also found in the European Household Panel Survey (Kyyra and Wilke, 2013), in the German Socio Economic Panel (Jürges, 2007), in the British Household Panel Survey (Paull, 2002) or in the 1990–1993 French Labor Survey (Magnac and Visser, 1999). While recall errors affect estimates of aggregate unemployment, they may also bias transition estimates. For example, Magnac and Visser (1999) find that employment durations corrected for recall errors are lower.

In the French LFS, it is not possible to correct classification errors: there are no reinterviews just after the first interview that control labor market status. However, we can address recall errors in the retrospective calendar. Unfortunately, Magnac and Visser (1999)'s method to correct for recall errors cannot be applied in our context. First, they assume that transition rates are constant over at least two years while we analyze higher frequency movements. Secondly, in the new LFS (since 2003), one individual situation is not observed both contemporaneously and with a one year-lag. This precludes the possibility of building Magnac and Visser's individual recall error matrix. However, in the new LFS (since 2003), different cohorts are interviewed in every month of the year. This higher frequency enables us to compare current transition rates and recalled transition rates, observed contemporaneously for different interview cohorts. We thus estimate the extent of recall bias. Based on those estimates, we then correct previous waves of the annual LFS (before 2002). Let us note that our method assumes that recall errors are not cyclical. Except for Akerlof and Yellen (1985), who suggest that the recall bias is less important when unemployment is increasing, there is little evidence that measurement errors are cyclically sensitive. In addition, Smith (2011) and Fujita and Ramey (2009) conclude that classification errors in transition rates do not induce a cyclical bias that could affect their analysis of unemployment volatility.

To better understand our method for computing recall bias, consider Table 1 which describes the LFS interview plan after the 2003 redesign. Each month, one individual is interviewed (in columns in the table) about her labor market status over the preceding year (dates are in rows). For example, the cohort interviewed in December 2006 (last but one column) reports their labor market status from January 2006 to December 2006. The interview scheme is such that, for one calendar month (or date), 12 cohorts report their labor market status. For example, cohorts interviewed from January 2006 to December 2006 declare their labor market status prevailing in January 2006 (second row). Out of those 12 cohorts, situations reported by the January 2006 cohort are the least biased and can be considered accurate. Labor market outcomes of January 2006 are reported by individuals surveyed in January 2006 (without recall error) and in February 2006 (with one month recall error). The differences observed between the two reports are, in our view, due only to the one lag recall error. We repeat the procedure for 2-month, 3-month, … recall error for January 2006 and consider February 2006, etc … We thereby obtain a time-series for one-month, two-month, three-month, etc., recall errors and estimate the average recall error for each lag using OLS.

In Fig. 1, we illustrate the extent of the recall bias for the unemployment rate, the separation rate and the finding rate. The first point gives the average for all cohorts of the contemporaneous declaration. If we denote the unemployment rate declared by the c cohort about month t U_t^c, the first point in the graph is $\sum_m U_{t=m}^{c=m}$. We consider this estimate as the truth. Thus the unemployment rate is 11% on average from January 2004 to December 2009. The second point is the unemployment rate recalled with a one-month lag ($\sum_m U_{t=m}^{c=m+1}$). As can be seen in Fig. 1, it is lower than the contemporaneous U rate. However, the difference is quantitatively small and not statistically significant. The one lag recall error estimate is shown in the first row and first column of Table 8 in Appendix B with its standard error. Table 8 shows that unemployment, separation and finding recall errors are all statistically significant from the six-month lag onwards, which means that individuals actually tend to forget episodes of separations and findings.

Fig. 1 shows that the recalled unemployment, separation and finding rates are generally decreasing with the recall lag. Notice also that the correction of separation is relatively greater than the one applied to finding rates. In Fig. 1, the

Table 1
Interview scheme of the new LFS (since 2003).

Date/cohort	Dec 2005	Jan 2006	Feb 2006	Mar 2006	Apr 2006	May 2006	Jun 2006	Jul 2006	Aug 2006	Sep 2006	Oct 2006	Nov 2006	Dec 2006	Jan 2007
Dec 2005	X	X	X	X	X	X	X	X	X	X	X	X		
Jan 2006		X(a)	X(b)	X(c)	X(d)	X(e)	X(f)	X(g)	X(h)	X(i)	X(j)	X(k)	X(l)	
Feb 2006			X	X	X	X	X	X	X	X	X	X	X	X
Mar 2006				X	X	X	X	X	X	X	X	X	X	X
Apr 2006					X	X	X	X	X	X	X	X	X	X
May 2006						X	X	X	X	X	X	X	X	X
Jun 2006							X	X	X	X	X	X	X	X
Jul 2006								X	X	X	X	X	X	X
Aug 2006									X	X	X	X	X	X
Sep 2006										X	X	X	X	X
Oct 2006											X	X	X	X
Nov 2006												X	X	X
Dec 2006													X	X
Jan 2007														X

X indicates that the cohort (in columns) is interviewed about its labor market status (in rows). X(a): interviewed in January 2006 about labor status in January 2006 (No recall error). X(b): interviewed in February 2006 about labor status in January 2006 (1-month recall error). etc … X(l): interviewed in December 2006 about labor status in January 2006 (11-month recall error). Estimate of 1-month recall error for January 2006: transition rate X(b) – transition rate X(a)… Estimate of 11-month recall error for January 2006: transition rate X(l) – transition rate X(a). Repeat the measurement of recall error for another date (February 2006, March 2006, etc …).

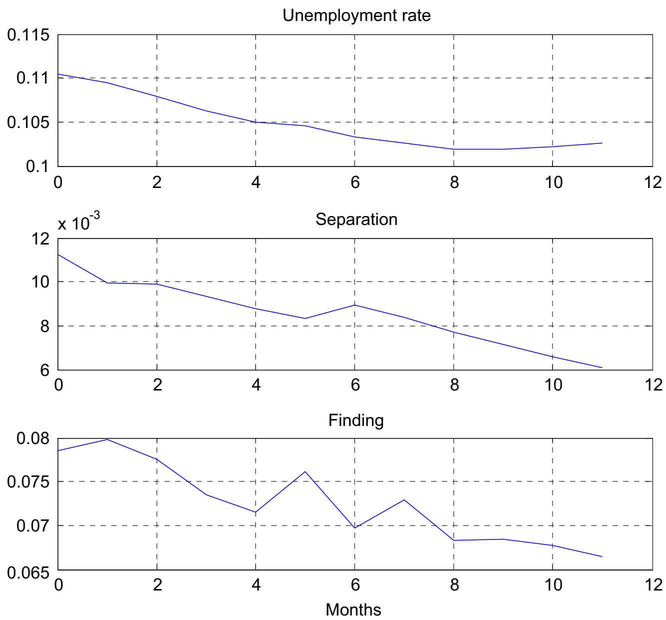

Fig. 1. Labor market outcomes by recall lags. LFS. Average computed for cohorts from January 2006 to December 2009.

separation rate is nearly divided by 2 between the 0 recall and the 11-month recall lag while the effect is relatively smaller for the finding rate (that bears a 20% fall, from approximately 8% without recall to 6.5% with a 11-month lag). Fig. 1 is consistent with studies stressing that memory decays linearly with the time distance between the event and the interview date (see Manzoni et al., 2011; Koskinen et al., 2012 for a survey). Let us notice that the more prevalent recall errors are on separations. It is consistent with the view that socially undesirable events tend to go unreported whereas socially desirable events are often over-reported (Pyy-Martikainen and Rendtel, 2009; Paull, 2002). For work status, employment and unemployment are respectively the most and least desirable categories. Hence, the state of being unemployed might be more prone to be wrongly reported.

We use the post-2004 recall error estimates to correct the LFS before 2002. For the LFS before 2002, there is only one cohort interviewed each year, namely in March, so that contemporaneous rates are available only once a year. To recover unbiased estimates, recalled outcomes are corrected with the post-2004 estimates.

Table 2
From gross flows to instantaneous transition rates.

	FH	LFS
Periods	1994Q1–2010Q4	1990Q2–2002Q1 2004Q1–2010Q3
1. Monthly gross flows N_t^{AB}	External source E	
2. Correct for recall error		Yes
3. Seasonally adjust the time series (x12)	Yes	Yes
4. Correct for time aggregation	Yes	Yes
5. Quarterly averages	Yes	Yes

Table 3
Average job separation and job finding probabilities.

Data	Separation prob. $\overline{\Lambda}^{EU}$ (%)	Finding prob. $\overline{\Lambda}^{UE}$ (%)
FH (administrative data)	1.7	13.5
LFS	1.2	7.5

2.4. Job finding and job separation rate series

The monthly instantaneous rates are converted to quarterly frequency by simple averaging, after seasonal adjustment and correction for time bias. We then use both HP filtering and first-order difference (FOD) as methods for detrending data. Adopting the detrending techniques already used in previous studies is very helpful for direct comparison and then the evaluation of how different the French labor market is from other countries.[9] Table 2 summarizes the steps involved in this process.

Table 3 shows average separation and finding transition probabilities across datasets. Whatever the dataset, the French worker flows are characterized by lower values of the job finding and separation rates than the ones computed on US data. Shimer (2012) and Fujita and Ramey (2009) find a job finding probability of around 30% and a separation probability of around 2%. Using the LFS, the French job finding probability amounts to $\overline{\Lambda}^{UE} = 7.5\%$. This value is consistent with an unemployment spell of 13.4 months. It nearly matches the OECD estimate of 14 months (average duration of unemployment, total, annual data from 1990 to 2009). The separation probability is $\overline{\Lambda}^{EU} = 1.2\%$. The LFS estimates are close to Elsby et al. (2013)'s results on outflows and inflows rates using annual data.[10] They show in France an average outflow rate of 7.7% and inflows of 0.7% (1975–2009). On the other hand, the transition rates using the administrative records are higher, but still far from their US counterparts. The difference in the finding rate between the LFS and FH datasets can be explained by the fact that some unemployed, who are not registered in the PES, are still in the LFS. Those not registered unemployed are typically "discouraged" workers who do not use the Employment Agency services: they have lower job finding rates. On the other hand, some workers in job-to-job transitions can claim unemployment benefits (and thus have to register at the PES) without self-declaring as unemployed in the LFS, which can explain why the average separation rate is higher when considering administrative data.

Figs. 2 and 3 show the job finding probability Λ_t^{UE} and separation probability Λ_t^{EU} using administrative data (FH) and LFS respectively, along with the corresponding actual unemployment rate. Notice that the measure of the actual unemployment rate is consistent with the definition of unemployment specific to each dataset. Indeed, unemployment is defined as inclusion in the register without employment in the FH, and self-reported unemployment in the LFS.[11] The stock of unemployed workers from each dataset is actually greater than the one meeting ILO criteria. As a result, the unemployment rate computed from each dataset differs from the ILO unemployment rate. When we refer to "actual" unemployment, we mean the actual unemployment rate computed from each dataset. Appendix C shows that changes in our "actual" unemployment rates are consistent with the ones observed for the ILO unemployment rate (with a correlation between both time series of approximately 0.98 for the FH and LFS).

In Figs. 2 and 3, unemployment dynamics display high volatility due to subsequent booms and busts. Overall, combining the two datasets, the data span two severe recessions (1990Q4–1994Q2 and 2008Q1–2009Q4) and one mild recession at the beginning of the 2000s (2001Q4–2004Q1) on the one hand and two expansions (1999Q1–2001Q4 and 2006Q1–2007Q4) on

[9] Shimer (2012) uses the HP filter with smoothing parameter 10^5 while Petrongolo and Pissarides (2008), Elsby et al. (2013) and Smith (2011) favor FOD. Fujita and Ramey (2009) use both.

[10] Note that the estimates are not directly comparable, as we consider job finding and separation rates, while Elsby et al. (2013) compute outflows and inflows rates. Using administrative data, Petrongolo and Pissarides (2008) find that the outflow and inflow rates from the PES are 14% and 1.5% (1991–2007), which are not significantly different from our FH results.

[11] In the US CPS, unemployment is associated with the job search (the survey defines unemployment status as "unemployed-looking for a job"). In the French LFS retrospective calendar, there is no information on the job search associated with the unemployment status. The survey respondent can report himself as unemployed, whatever his actual job search behavior.

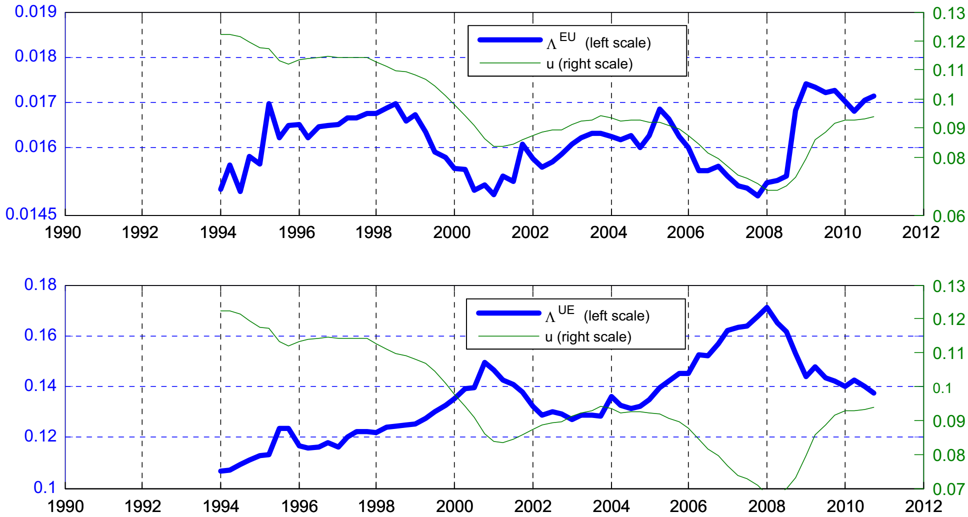

Fig. 2. Administrative data (FH): Transition probabilities (separations Λ^{EU} in the upper part, findings Λ^{UE} in the lower part) and actual unemployment rate (u).

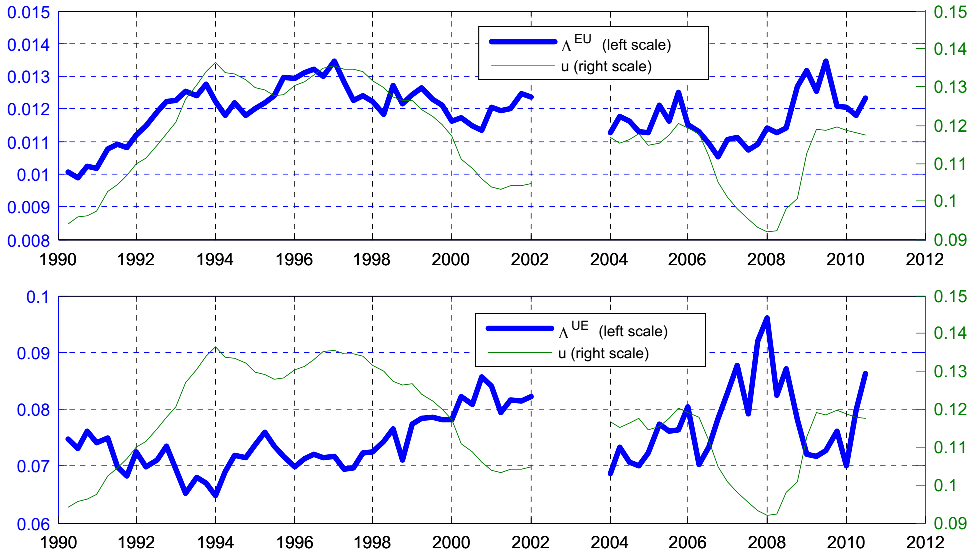

Fig. 3. LFS: Transition probabilities (separations Λ^{EU} in the upper part, findings Λ^{UE} in the lower part) and actual unemployment rate (u).

the other hand.[12] Furthermore, a steady dynamic can also be observed between 1995 and 1999. Both transition rates fluctuate with unemployment: the job finding rate negatively moves with unemployment, whereas the separation rate is positively correlated. At this stage, it is difficult to conclude that a particular transition rate contributes more to unemployment volatility than the other. Considering administrative data, the cyclical swings of the transition rates perfectly mirror those of unemployment. The separation rate jumps to relatively high values in recessions, and decreases by a large amount in expansions. The opposite is true for the job finding rate. For the LFS data, the rate dynamics are more erratic and, at least visually, less cyclical. However, this statement is less true during the last two cyclical episodes.

3. Quantitative analysis of the unemployment volatility

Our objective is now to examine the contributions of the transition rates to unemployment fluctuations, more precisely, to give a quantitative measure of the relative contribution of the separation rate and the finding rate. This analysis is firstly based on the dynamics of steady state unemployment. Acknowledging that this approach is only valid when the transition rates are high enough, a non-steady state analysis is then also proposed.

[12] A recession (an expansion) is considered as a continuous increase (decrease) in ILO unemployment.

3.1. Analysis of steady state unemployment

In order to examine the cyclicality of the job finding and separation rates, Shimer (2012) uses Eq. (1) to infer the expression of the steady state unemployment rate. Using the assumption about the lack of transition in and out of the labor force, $e_{t+\tau}=1-u_{t+\tau}$, we obtain the expression of the steady state unemployment rate:

$$u_t^{SS}=\frac{\lambda_t^{EU}}{\lambda_t^{EU}+\lambda_t^{UE}} \tag{6}$$

On US data, Eq. (6) provides a very good approximation of the end-of-period actual unemployment rate with a correlation between u_t^{SS} and the actual unemployment rate of 0.99. On French data, the correlation is lower (respectively equal to 0.91 and 0.83 for FH and LFS data) but we consider that it is high enough to preserve the relevance of the steady state approach, at least as a first strategy before considering a non-steady or dynamic analysis (Section 3.3).

Using this strong relationship between actual unemployment and steady state unemployment, fluctuations in the equilibrium unemployment rate can be broken down into changes in the separation rate λ_t^{EU} and the job-finding rate λ_t^{UE}. Along the lines of Shimer (2012), we compute the following hypothetical steady state unemployment rate that holds the separation or the job finding rates constant at their historical averages:

$$u_t^{SS\_UE}=\frac{\overline{\lambda}^{EU}}{\overline{\lambda}^{EU}+\lambda_t^{UE}} \tag{7}$$

$$u_t^{SS\_EU}=\frac{\lambda_t^{EU}}{\lambda_t^{EU}+\overline{\lambda}^{UE}} \tag{8}$$

where $\overline{\lambda}^{EU}$ and $\overline{\lambda}^{UE}$ denote the average values of separation and finding rates respectively.

In order to provide a single measure of the contribution of each rate to the changes in unemployment, the method consists in regressing each log-detrended counterfactual steady state unemployment, $du_t^{SS\_UE}$ and $du_t^{SS\_EU}$, on log-detrended steady state unemployment du_t^{SS}:

$$\beta^{UE}=\frac{cov(du_t^{SS},du_t^{SS\_UE})}{var(du_t^{SS})} \tag{9}$$

$$\beta^{EU}=\frac{cov(du_t^{SS},du_t^{SS\_EU})}{var(du_t^{SS})} \tag{10}$$

Petrongolo and Pissarides (2008), Elsby et al. (2013) and Fujita and Ramey (2009) prefer to decompose changes in unemployment dynamics into two linear terms, corresponding to the relative contribution of the two transition rates. They rely on the following approximation of steady state unemployment:

$$\log\left(\frac{u_t^{SS}}{\overline{u}^{SS}}\right)=(1-\overline{u}^{SS})\log\left(\frac{\lambda_t^{EU}}{\overline{\lambda}^{EU}}\right)-(1-\overline{u}^{SS})\log\left(\frac{\lambda_t^{UE}}{\overline{\lambda}^{UE}}\right)$$

The contribution of the separation (finding) rate is then obtained by regressing the first (second) component of the right-hand side on the deviation of steady state unemployment from its trend. This is an exact variance analysis, whereas Shimer's method is not. Actually, these two methods lead to the same results for the US labor market, when the same detrending method is used in both cases (Appendix D). We obtain the same equivalence on the French economy.

On the other hand, the results are quite sensitive to the detrending method. Shimer (2012) uses an HP filter with a relatively high smoothing parameter (equal to 10^5), which corresponds to a much lower-frequency filter than commonly used in the literature. Fujita and Ramey (2009) uses in turn an HP filter with standard smoothing parameter (1,600) and a first-difference filter. Actually, reconsidering the transition rates for the US, in Appendix D, shows that different detrending method lead to changes in the contribution estimates by around 15 points, which is consistent with the results presented in Fujita and Ramey (2009). This is why the results for both HP filter with smoothing parameter of 10^5 and first order differentiation will be discussed hereafter.

Figs. 4 and 5 plot the HP detrended dynamics of the two hypothetical unemployment rates ($du_t^{SS\_EU}$) and ($du_t^{SS\_UE}$) relative to the HP detrended component of the steady state unemployment.[13] In the first 1990Q4–1994Q2 recession, considering only the LFS data, both rates appear to explain the rise in unemployment (Fig. 5). This balanced contribution also characterizes the first 1999Q1–2001Q4 expansion featured by a decline in unemployment, whatever the dataset considered. The steady period 1994–1999 confirms this balanced impression. However, the job finding rate during the expansion 2006Q1–2007Q4 appears more active in the decrease in the unemployment rate in both Figs. 4 and 5: more unemployment

[13] The counterfactual (or hypothetical) steady state unemployment rates when using the HP filter allow us first to visualize the relative cyclicality of the two transition rates. Note that first differentiated series are visually less interpretable. They are presented in Fig. 15 Appendix D.

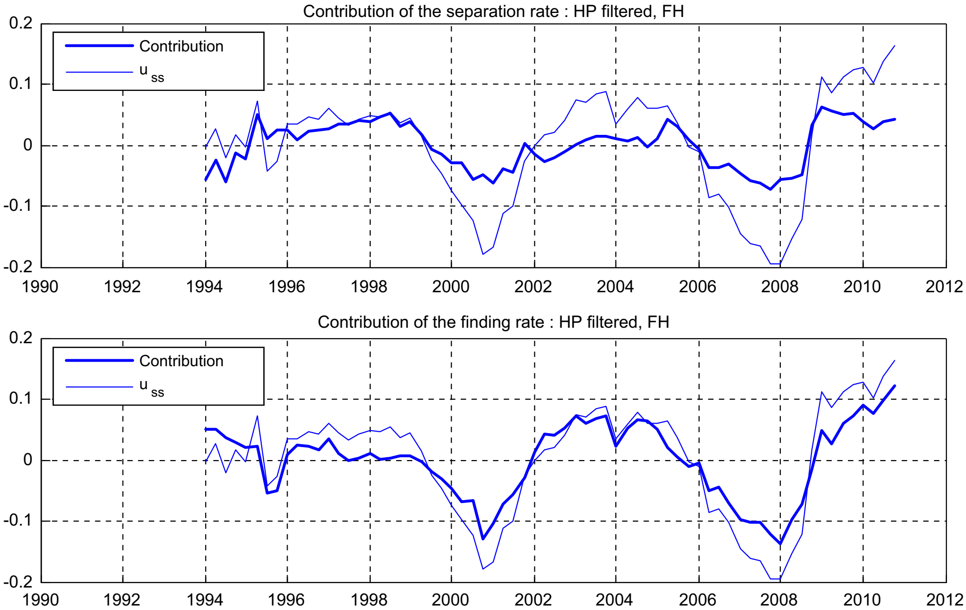

Fig. 4. Administrative data (FH): contribution of the separation (upper part, $du_t^{SS\_EU}$) and finding (lower part, $du_t^{SS\_UE}$) rates (in bold) to steady state unemployment (du_t^{SS}).

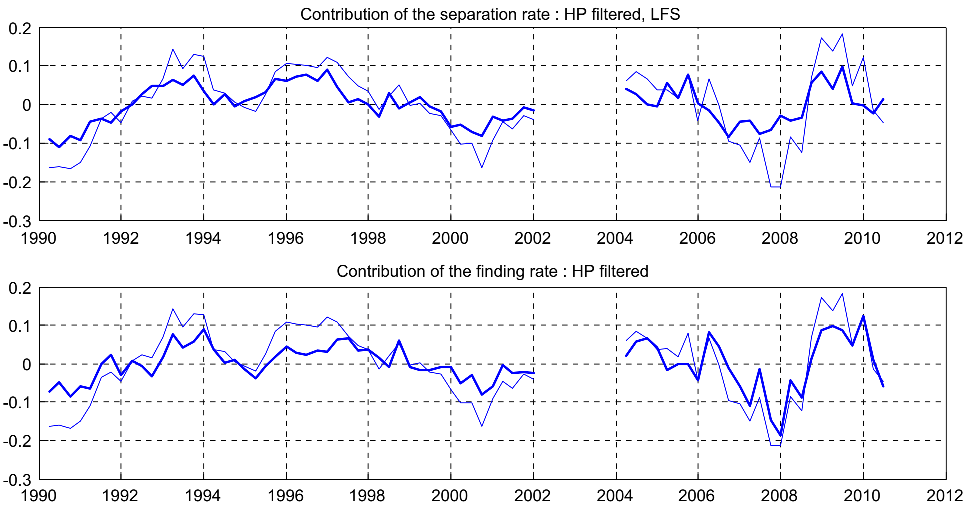

Fig. 5. LFS: contribution of the separation (upper part, $du_t^{SS\_EU}$) and finding (lower part, $du_t^{SS\_UE}$) rates (in bold) to steady state unemployment (du_t^{SS}).

outflows result in a lower unemployment rate. The importance of the job finding rate seems even greater during the 2008Q1–2009Q4 recession: the surge in steady state unemployment is closely matched by a falling job finding rate. Notice that this apparent change in the relative contribution of the job finding rate at the end of the 2000s was already present during the cyclical episode at the beginning of this decade (Fig. 4).

Table 4 shows the quantitative contribution of the separation rate β^{EU} and of the job finding rate β^{UE} (in parenthesis). Overall, the results are quite robust to the detrending method used.[14] The contribution of the job finding rate β^{UE} is almost exactly the complement to 1 of β^{EU}. Firstly, let us consider the results for the administrative data. In the period 1994–2010, the job finding rate explains between 57 and 64% of the unemployment cyclical variations, depending on the detrending method (column (4), lines 1 and 2). This share is more balanced [48,53] when considering the last years of the 1990s (column (2), lines 1 and 2). These results are confirmed when considering LFS data: the job finding rate becomes the dominant contributor to the unemployment dynamics in the 2000s ([65,72], column (3), lines 3 and 4), whereas both

[14] Moreover, the HP results are not systematically biased in favor of the job finding contribution as in the US. We comment this point at the end of Section 3.3.

Table 4
Contribution of the separation rate (β^{EU}) and of the job finding rate (β^{UE}, in parenthesis) to fluctuations in steady state unemployment.

Period		1990–2002 (1)	1994–2002 (2)	2004–2010 (3)	1994–2010 (4)
FH	1. HP	NA	52 (47.9)	35 (64.9)	35 (64.2)
	2. FOD	NA	46.8 (53.5)	42.3 (57.6)	42.7 (57.3)
LFS	3. HP	55.5 (44.6)	51.9 (48.1)	35.5 (64.5)	NA
	4. FOD	34.3 (65.7)	41.3 (58.5)	28 (72)	NA

Note: NA: Not Available. HP: HP filtering with smoothing 10^5. FOD: First-order Difference. FH: Fichier Historique (administrative data). LFS: Labor Force Survey. The contribution over the period 1994–2010 (line 1, column 4) is not a weighted mean of the contributions over the 2 sub periods 1994–2002 and 2004–2010 (columns 2 and 3) as 7 quarters are missing (2002Q2–2003Q4).

transition rates played an important role in the previous decade.[15] Let us emphasize that these features are representative of the unemployment volatility. Indeed, Appendix E shows on LFS data that the job separation and job finding rates are the major contributors to unemployment dynamics: flows involving exit from or entry to labor force explain a very weak part of unemployment volatility, whatever the detrending method.

The job finding rate dominates the unemployment fluctuations, especially on the most recent cyclical episodes. Since Shimer (2012)'s paper, researchers have found a substantial contribution of separation rates in unemployment dynamics (between one-third and one-half, Fujita and Ramey, 2009; Elsby et al., 2009 in the US, Smith, 2011; Gomes, 2012 in the UK, Silva and Vazquez-Grenno, 2013, in Spain). In the range of results found in the literature, France therefore stands out as a country in which job finding influence on unemployment fluctuations has been particularly dominant in recent years. However, the job separation rate cannot be overlooked in France, at least in the 1990s. It is certainly because recessions give way to cleansing reallocations. It could even be that recessions provide legal opportunities to French firms to scale down their staff.

Finally, let us note that the contribution of the separation rate would have been found significantly higher without removing recall errors: 62.7% between 1990 and 2002 and 40.9% between 2004 and 2010, which would have made the results from the two datasets more divergent (See Table 9 in Appendix B). Intuitively, the dominant effect is the following: uncorrected separation rates exhibit a much lower mean, as socially undesirable events tend to go unreported whereas socially desirable events are often over-reported (Pyy-Martikainen and Rendtel, 2009; Paull, 2002). This implies larger deviations from the uncorrected mean of separation rates, and hence a more significant contribution of separation volatility in the fluctuations of steady state unemployment when recalls errors are not removed. The recall error correction we implement proves to be an important piece of our strategy.

3.2. *Labor market duality*

There are obviously different ways to interpret the increasing importance of the job finding rate. A natural candidate is the rising prevalence of the temporary contracts in the French labor market. During the period 1998–2007, the vast majority of (quarterly) flows from unemployment to salaried employment, almost 80% of new job findings, were under temporary contracts (Bentolila et al., 2012). They are used by firms to circumvent employment protection laws and screen workers, especially young workers. Our intuition is that the purposes of this type of contract make separation more independent of the business cycles, thereby limiting its cyclical volatility. As long as the term is not reached, separations from temporary contracts are not common (Cahuc et al., 2012). They happen without any penalties at the term of the contract. There are also legal constraints in the renewal procedure: temporary contacts can only be renewed once and the time spent on the job cannot exceed two years. The increased prevalence of temporary contracts can then reduce the fluctuations in the separation rate through a classical composition effect, as long as the cyclicality of the separation rate is very heterogenous across temporary and permanent contracts.

It is then worth investigating this heterogeneity across labor contracts. Unfortunately, it is not possible to conduct an analysis along the lines described in the previous section. Although we can use the Labor Force survey to disentangle current employment between temporary (short-term S) and permanent (long-term L) contracts, this information is not reported in the retrospective calendar of the labor force survey. This means that we have to rely on the panel data structure of the quarterly survey to compute transitions. Recall that this panel has been available only since 2003. For every individual interviewed over two consecutive quarters, we observe their contemporaneous labor market status, along with the type of

[15] However, let us note that including the deep recession at the beginning of the nineties (column (1) in Table 4) *and* considering first-order differentiated series leads to a dissonant weakness of the job separation contribution during the 1990–2002 period, which would decline to one-third (column (1), line 3 compared with line 4). This is due to a particular pattern of the separation rate over the 1991–1993 recession episode: the cumulated response of unemployment induced by the separation rate variations slowly increases over this period, but some quarter-to-quarter variations are negatively correlated with those in unemployment. This high frequency pattern leads to a reduction of the contribution of the separation rate to unemployment dynamics when series are filtered by first order differentiation. We can expect that taking into account deviations from unemployment steady state will smooth the unemployment dynamics and then help to deliver a rather homogenous contribution of the separation rate across detrending method. It will be the case, as can be seen in Table 7.

Table 5
LFS. Quarterly transition matrix (Λ) averaged over 2004–2011.

Status in $t-1$	Status in t		
	Unemployment	Temporary contract	Permanent contract
Unemployment	.	0.178	0.079
Temporary contract	$0.119_{(a)}$	.	0.074
Permanent contract	0.008	0.005	.

Labor status in quarter $t-1$ in column. Labor status in quarter t in line. (a): The transition probability from Temporary Contract to Unemployment is 11.9%.

labor market contract. This quarterly frequency is the first difference from the previous analysis. The second difference, and rather a limit for the panel data approach, is that we have to restrict our attention to individuals without geographic mobility (because the survey loses track of movers), whereas all individuals who were surveyed once were included in the previous analysis (because the retrospective calendar is filled in at the *first* interview). So the sample in the analysis based on retrospective calendars is based on a larger number of individuals since the measurement of quarterly transitions suffers from attrition due to movers. This can bias the measure of transitions and their relative importance. The last difference is that unemployment status in the quarterly panel is based on the ILO definition whereas labor market states in the retrospective calendar are subjective reports.[16]

Although the relative importance of separation and finding rates is not necessarily comparable between the two approaches, we disentangle labor market contracts in order to provide some first empirical evidence on their strong heterogeneity in terms of separation and finding rates. We compute the weighted gross flows between the three states (U, L and S), and then the quarterly transition rates over the period 2004–2011 after correcting for time aggregation bias using the Shimer (2012) formula for the 3 state analysis.

Table 5 shows the average quarterly transition probabilities over the period 2004–2011. The highest transition probabilities involve temporary contracts (S): 17.8% of unemployed workers find a temporary job over the quarter and 11.9% of workers lose their temporary job over the same period. The job finding probability for permanent contract (L) is only half the temporary job finding probability (7.9% vs. 17.8%). In other words, around two-thirds of hirings (from the pool of unemployed workers) are on temporary jobs. Transitions from temporary to permanent contracts are slightly less frequent than transitions from temporary contracts to unemployment (7.4% vs. 11.9%). Some of these transitions occur within the firm. In this case, the contract is converted by the firm and it is likely that the temporary contract has been used as a screening device (although this is not a legal reason to use it). More generally, these transitions are consistent with the idea that temporary jobs are stepping stones to permanent jobs. The transition probability from permanent contracts to unemployment is as expected very low 0.8%, but the transition probability from permanent to temporary contracts is even lower: workers separating from permanent jobs usually receive unemployment benefits which enable them to search for higher quality jobs. In the main text, the average quarterly job finding probability computed with the retrospective calendar (around 24%$=3\times$8%) is consistent with the one implied by Table 5 (more than 25%).

Fig. 6 shows the evolution of the different transition probabilities over the period 2004–2011 compared to the actual unemployment rate. As expected, transitions probabilities to unemployment both from temporary and permanent contracts are counter-cyclical (first row) and transition probabilities from unemployment to both types of jobs are pro-cyclical. It is not clear which employment type contributes the most to unemployment volatility, although the transition probabilities from permanent job to unemployment seems to better follow the increase in unemployment during the Great Recession. There is a clear decrease in both S-L and L-S transition probabilities during the Great Recession.

To quantify the importance of the transition rates to unemployment volatility, we compute contributions following Shimer (2012)'s 3-state model (unemployed, employed on a temporary job, employed on a permanent job). We then compute six counterfactual unemployment rates. In each of them, all transition rates are set constant at their period average except one. To quantify the contributions, we regress the cyclical component of each hypothetical unemployment rate on that of the steady-state unemployment rate. The contributions of the flows in and out of unemployment shown in Table 6 are clearly heterogenous across contract types (first vs. second column). We do not report the contributions of the transitions between jobs, which sum to zero. The contribution of the transition rate from permanent contract to unemployment is higher than that from temporary contracts (49% vs. 12%). This difference is not far from the relative weight of permanent and temporary contracts in the employment stock (around 15%). On the other hand, the contribution of the job finding rate through temporary contracts is far beyond their relative weight. The rise in the share of temporary contract employment can then explain the relative rise in the contribution of the finding margin observed over the last decade. However, we acknowledge that these results must be taken with caution due to the data limitations listed above.[17]

[16] In particular, unemployment status is not necessarily associated with an active job search.

[17] Finally, note that adding β on separations and β on hirings does not yield the same figures as in the previous section. Separations seem to contribute more than findings, whereas we obtain the opposite in the previous section. Again, this might be due to the differences in samples and data limitations listed above.

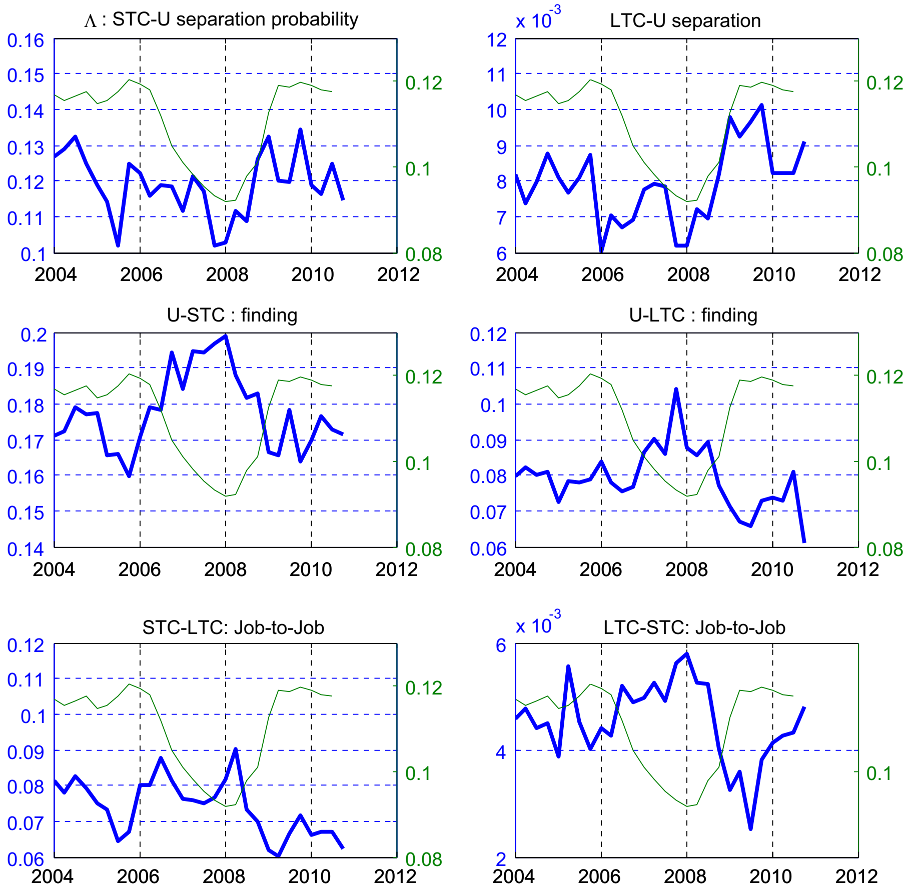

Fig. 6. Quarterly transition probabilities (bold, left scale) and actual unemployment rate (right scale, LFS). STC: Short-Term Contract; U: Unemployment. LTC: Long-Term Contract.

Table 6
LFS. Contribution of the transition rates to unemployment fluctuations.

	Temporary contract	Permanent contract	Sum
Job separation			
HP	0.12	$0.49_{(a)}$	0.61
FOD	0.12	0.57	0.69
Job finding			
HP	0.16	0.25	0.41
FOD	$0.10_{(b)}$	0.20	0.30

(a) 49% of unemployment fluctuations are explained by changes in the job separation rate from permanent contract to unemployment. HP filtered time series. (b) 10% of unemployment fluctuations are explained by changes in the job finding rate from unemployment to temporary jobs. FOD time series.

Silva and Vazquez-Grenno (2013) perform a similar exercise on Spanish data over a longer time period (1987–2010). Contrary to our results, they find that "the transition rates involving temporary employment account for around 60% of the fluctuations in the unemployment rate". Those opposing results point to different use of temporary contracts between the two countries. Indeed temporary contracts are much more prevalent in employment stocks in Spain (one third vs. less than 15% in France). As noticed by Blanchard and Landier (2002), the rather stringent rules governing temporary contracts in France (conditions, duration, nonrenewal) imply that their proportion has not reached the levels observed in Spain. However, we share with Silva and Vazquez-Grenno (2013) that temporary employment plays a more important role in job finding than in job separation on the one hand and that the positive contribution of the transition rate from temporary to permanent jobs fluctuations is canceled out by the transition rate from permanent to temporary jobs on the other hand.

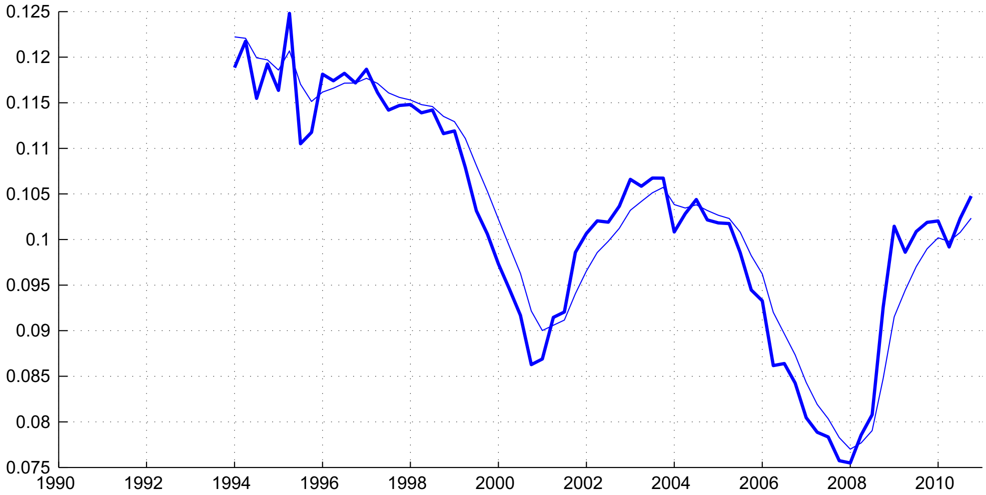

Fig. 7. Administrative date (FH): steady state unemployment (u^{SS} in bold) vs. actual unemployment (u).

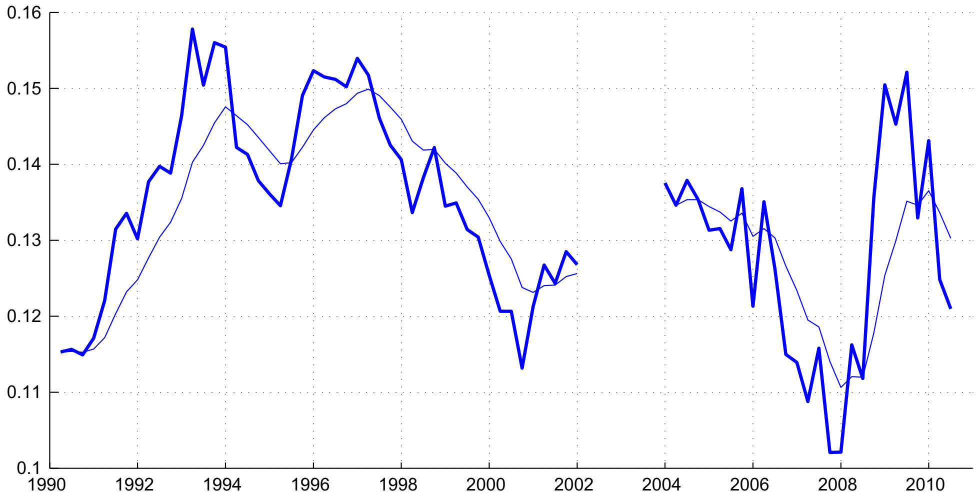

Fig. 8. LFS: Steady state unemployment (u^{SS} in bold) vs. actual unemployment (u).

3.3. *Analysis of actual unemployment*

Because of low inflow and outflow rates, actual unemployment may not be well proxied by its steady state value. Indeed, comparing the steady state and the actual unemployment rates in Figs. 7 and 8 shows that the former lead the latter around the business cycle turnovers, when unemployment is changing fast.

We then consider the unemployment dynamics implied by Eq. (1), which takes into account the deviations from the unemployment steady state. Consistently on the method we used in the static analysis case, we consider the hypothetical unemployment dynamics using Eq. (1) that hold the separation or the job finding rates constant at their historical averages. Unemployment variation is the result of contemporaneous changes in the separation and finding rates or the result of dynamics driven by past changes in these flow hazards.

More precisely we first integrate Eq. (1) over 3 months (instantaneous transition rates are averaged over one quarter). This yields the following law of motion of the quarterly unemployment rate (in the following t stands for quarter):

$$u_t = \left(1-\exp\left(-3(\lambda_t^{EU}+\lambda_t^{UE})\right)\right)\frac{\lambda_t^{EU}}{\lambda_t^{EU}+\lambda_t^{UE}}+\exp\left(-3(\lambda_t^{EU}+\lambda_t^{UE})\right)u_{t-1} \tag{11}$$

with u_t the unemployment rate observed at the end of the final month in quarter t. Note that high inflow and outflow rates imply that the unemployment rate is close to its steady state. Secondly the hypothetical unemployment rates that hold the

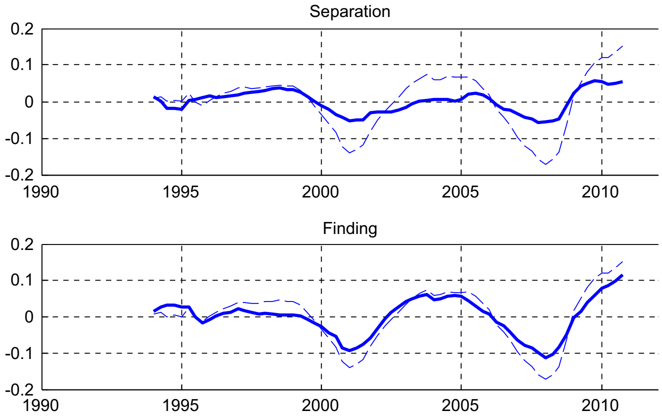

Fig. 9. Administrative data (FH): contribution of the separation (upper part, du_t^{EU}) and finding (lower part, du_t^{UE}) rates (in bold) to actual unemployment (du_t). HP filter with smoothing 10^5.

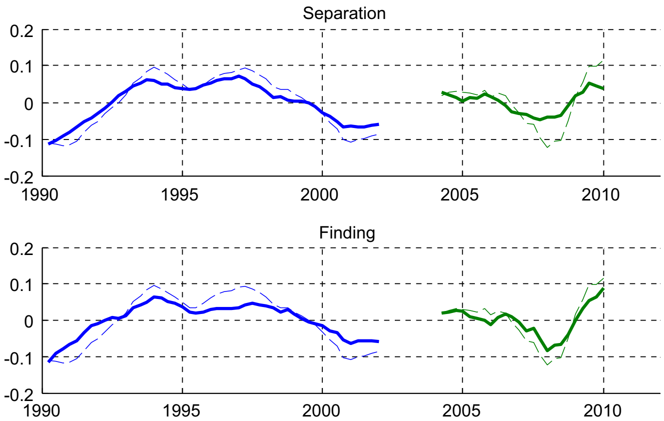

Fig. 10. LFS: Contribution of the separation (upper part, du_t^{EU}) and finding (lower part, du_t^{UE}) rates (in bold) to actual unemployment (du_t). HP filter with smoothing 10^5.

separation or job finding rate constant ($\overline{\lambda}^{EU}$ and $\overline{\lambda}^{UE}$) are computed recursively using:

$$u_t^{EU} = \left(1-\exp\left(-3(\lambda_t^{EU}+\overline{\lambda}^{UE})\right)\right)\frac{\lambda_t^{EU}}{\lambda_t^{EU}+\overline{\lambda}^{UE}}+\exp\left(-3(\lambda_t^{EU}+\overline{\lambda}^{UE})\right)u_{t-1}^{EU} \tag{12}$$

$$u_t^{UE} = \left(1-\exp\left(-3(\overline{\lambda}^{EU}+\lambda_t^{UE})\right)\right)\frac{\overline{\lambda}^{EU}}{\overline{\lambda}^{EU}+\lambda_t^{UE}}+\exp\left(-3(\overline{\lambda}^{EU}+\lambda_t^{UE})\right)u_{t-1}^{UE} \tag{13}$$

with initial unemployment rates defined as below:

$$u_0^{EU} = \frac{\lambda_0^{EU}}{\lambda_0^{EU}+\overline{\lambda}^{UE}} \tag{14}$$

$$u_0^{UE} = \frac{\overline{\lambda}^{EU}}{\overline{\lambda}^{EU}+\lambda_0^{UE}} \tag{15}$$

As in Elsby et al. (2013), iterating on both Eqs. (12) and (13) makes the actual unemployment rate dependent on current and past values of separation and finding rates. Figs. 9 and 10 are quite consistent with those relative to the steady state unemployment analysis. In the early part of the sample, cyclical unemployment is explained by the two hypothetical dynamics in a very similar way. The contribution of the job finding rate appears to rise at the end of the sample: job finding prospects seem to drive the 2006 expansion and the 2008 recession.

Table 7
Contribution of the separation rate β^{EU} (job finding rate β^{UE}) to fluctuations in actual unemployment.

Period	1990–2002	1994–2002	2004–2010	1994–2010
FH				
1. HP	NA	52 (44)	34 (65)	36 (65)
2. FOD	NA	42 (58)	41 (58)	39 (60)
LFS				
3. HP	56 (43)	55 (44)	40 (59)	NA
4. FOD	51 (49)	52 (48)	34 (65)	NA

Table 7 shows the estimated contribution of separations after implementing the dynamic analysis, which reflects the contributions of current *and* past variations in the transition rates to unemployment fluctuations. Technically speaking, the method consists in regressing detrended counterfactual unemployment on detrended actual unemployment, using the Hodrick–Prescott filter for detrending with a smoothing parameter of 10^5 as well as the first-order difference. Compared to the steady state decomposition (Table 4), Table 7 conveys the same picture of a balanced view on the relative contributions of the finding and separation rates in the 1990's, with a greater contribution of the job finding rate in recent years. Taking into account the unemployment dynamics leads to a slightly higher influence of the separation rate. This echoes Elsby et al. (2013)'s results on French data. But the differences with Table 4 are small.

Let us notice that, unlike French data, the dynamic decomposition on US data in Fujita and Ramey (2009) leads to different results from the steady-state decomposition. The reason lies in the cross-correlations at various lags and leads between the transition rates and unemployment rate. Elsby et al. (2009) note on US data that the separation rate displays sharp peaks at the start of recessions and then has long-lasting effects on unemployment dynamics. In addition, Fujita and Ramey (2009) find that the job separation rate is strongly negatively correlated with future changes in unemployment, which is not the case of the job finding rate.[18] Taking into account the dynamic interactions between transition rates substantially increases the importance of the separation rate in explaining unemployment variability. In contrast, we find no evidence of such dynamic asymmetries across transition rates in France: the peak is at the contemporaneous correlation for both separation and finding rates and the shape of cross-correlations with unemployment fluctuations is quite similar across the two transition rates (Appendix F). As the job finding rate does not tend to lag behind the separation rate, it is then expected to find similar results in the static and dynamic decompositions on French data. This is clearly an original feature of French labor market.

4. Beyond the unconditional analysis: a structural VAR approach

Fujita (2011) and Canova et al. (2012) have recently investigated the relative contribution of the finding and separation rates to the unemployment volatility generated by well-identified structural shocks. This approach is potentially of interest in order to identify the characteristics of the French economy. The latter is characterized by particular labor market institutions, such as duality in terms of contracts and generous unemployment benefits, among others. These particular features could lead to particular propagation mechanisms and to the existence of particular shocks. At the end, the unconditional features shown in the previous section could be a mix of quite different factors. This is why it is of particular interest to identify the relative contribution of the finding and separation rates conditional on well-identified shocks. This is a more structural approach which could deliver more insightful evidence on the French economy, especially on the dynamic relationships between transition rates and the unemployment rate.

As a first strategy, we adopt a very parsimonious approach and identify only one generic business cycle shock.[19] In order to be comparable with the US economy, we adopt exactly the same Bayesian Structural VAR methodology as in Fujita (2011), and the same trivariate system as well as the same sign restrictions. The trivariate system includes the separation and job finding rates and a vacancies series. We use the series of vacancies posted by the Public Employment Service available from 1997 onwards.[20] Given this time range, we choose to focus on transition rates measured in the FH administrative data (years 2002 and 2003 are missing from the LFS).

Let us emphasize that the behaviors of gross flows and stock of unemployment can be traced from the impulse response functions of the transition rates. The shock restrictions are as follows: as in Fujita (2011), we assume that in response to a negative shock, unemployment rises for 2 quarters, while vacancies drop in the impact period. Several shocks can be consistent with these restrictions, among others aggregate productivity shocks or aggregate demand shocks, all shocks that

[18] On US data, Fujita and Ramey (2009) show that the correlation between the separation rate and unemployment lies above 0.50 at lags of zero to four quarters, whereas the correlation between unemployment and the future separation rate are lower: they then conclude that the separation rate leads unemployment. On the other hand, the highest correlation between unemployment and the job finding rate is contemporaneous.

[19] We leave for further research the ambition to identify several structural shocks.

[20] The Ministry of Labor publishes a monthly seasonally adjusted series that we average over quarters. Until 2005, the French Public Employment Service had a monopoly on the placement of unemployed individuals and, at least in theory, a key role in labor market intermediation (all vacancies were supposed to be posted by the public employment services until 2005).

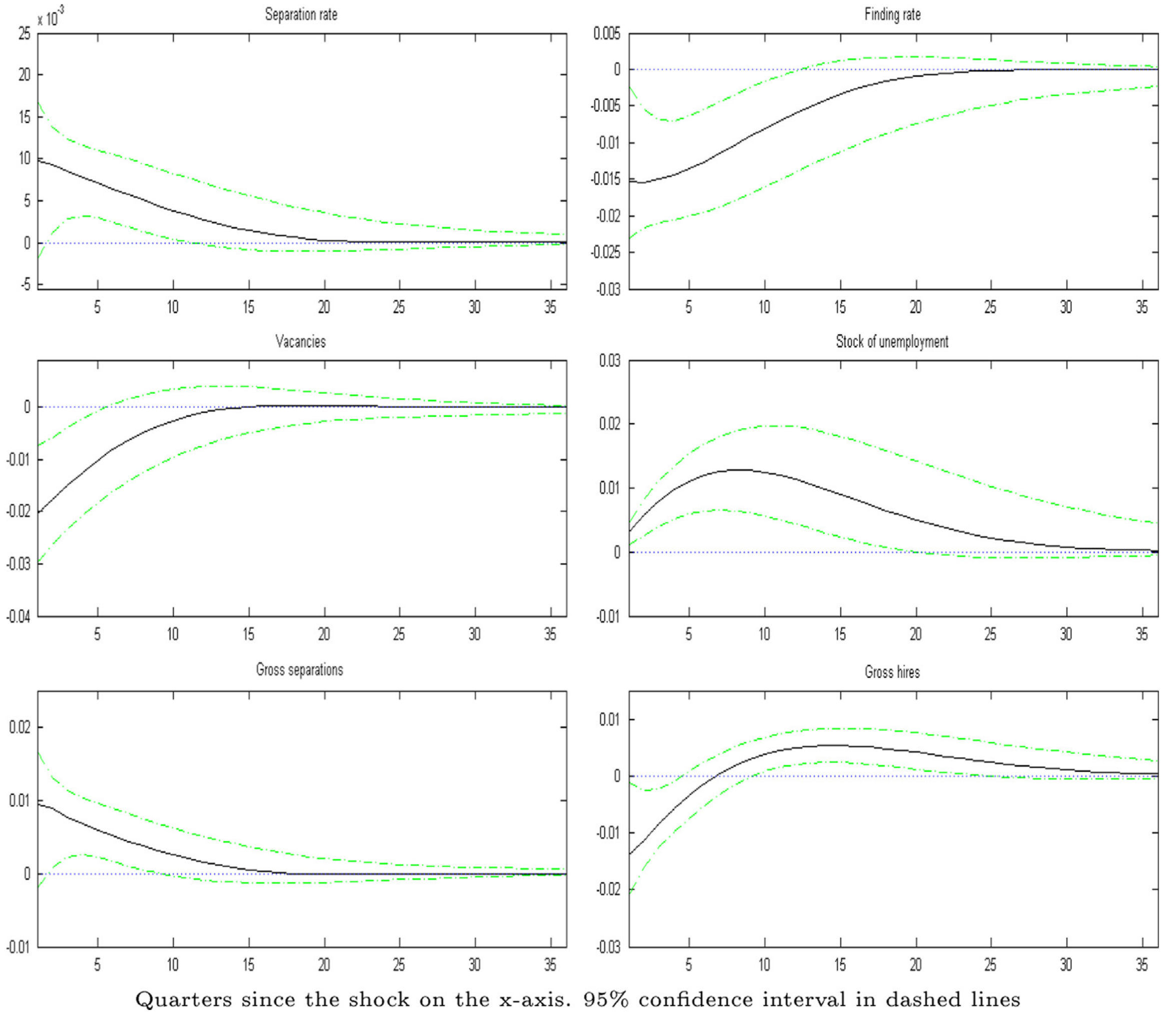

Fig. 11. Impulse response functions to a negative aggregate shock.

hit the employment surplus. This generality is clearly of benefit for our purpose, as we want to focus on quite "significant" business cycle shocks. Although there are some well-known limits to the use of this methodology[21], we believe that it can provide a reliable picture of the labor market flows generated by these aggregate shocks. More particularly, as the shock is identified without imposing any restrictions on the dynamics of the transition rates, it makes it possible to unveil their responses to this aggregate shock.

4.1. The impulse responses to a negative aggregate shock

After detrending the series with the Hodrick-Prescott filter[22] (with a smoothing parameter equal to 10^5), the trivariate VAR model is estimated with one lag according to Akaike information, Schwarz and Hannan–Quinn criteria. Fig. 11 displays responses of transition rates, worker flows, vacancies and unemployment. As in Fujita (2011), the three lines in the figures represent the 16th, 50th, and 84th percentiles of the simulated posterior distribution.

The impulse response functions on French data are consistent with the implications of the canonical search and matching model. A negative aggregate shock decreases the job surplus, implying fewer vacancies and more separations. This then leads to a significant lowering of the job finding rate and to a significant increase in the separation rate (Fig. 11), although the responses of the transition rates are not restricted *a priori*. These patterns in the transition rates explain why

[21] The sign restriction approach could lead to ambiguous results in the case of weak identification strategy. Fujita (2011) argues that, in his application, the identification scheme actually leads to unambiguous results since, following a negative aggregate shock, impulse response functions lead to the expected dynamics in gross hires and gross separations. These responses are also consistent with the estimated changes in separation and finding rates.

[22] The results are robust to the use of a quadratic trend as in Fujita (2011).

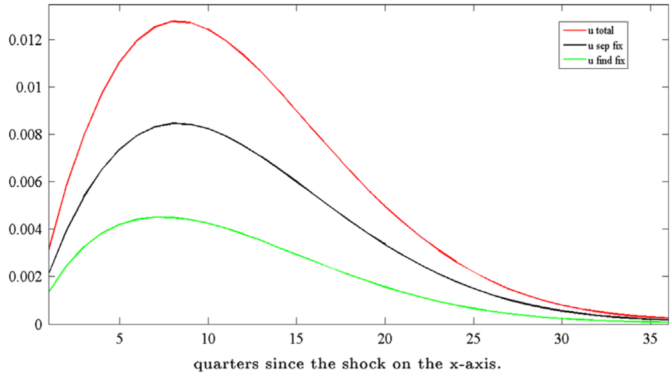

Fig. 12. The contribution of the finding and separation rates (IRF).

the stock of unemployment goes up in a persistent way. Moreover, persistence in transition rates appears higher in France, which seems consistent with previous analysis on French unemployment hysteresis.

Moreover, the response of the job finding rate is not delayed in France. The job finding rate declines more quickly in a French recession episode, and not gradually as in the US. The French separation rate does not lead labor market adjustments, unlike its US counterpart. As a result, there are no dynamic asymmetries across the transitions rates, which is consistent with the cross-correlation analysis (Appendix F) and the decomposition of actual unemployment fluctuations (Section 3.3). Moreover, in France, the job finding rate displays a larger deviation from the steady state than the separation rate, which is consistent with a higher contribution to unemployment dynamics. However, it would be wrong to conclude that the separation margin does not matter, as shown by the expansionary behavior of the gross hirings following the growth in the unemployment stock: the "pool size effect" outweighs the effect from slower job finding as emphasized by Fujita (2011).

4.2. *The relative contribution of the finding and separation rates*

It is possible to extend the hypothetical analysis proposed by Shimer (2012) to the IRF analysis along the lines of Fujita (2011), in which either the separation or the job finding rates is artificially fixed at its steady state level. We will focus here on the response of the unemployment stock and compare the contribution of the two transition rates. In Fig. 12 we can compare the two hypothetical paths of the unemployment stock with the estimated response where the two transition rates fluctuate: it can be seen that the contribution of the finding rate dominates that of the separation rate. However, both margins are quantitatively important and ignoring movements of the separation rate would generate highly counterfactual implications on the gross hirings.

In order to gain more insight into the quantitative importance of the two margins, using Eqs. (9) and (10), we calculate the beta coefficient from simulated series conditional to the aggregate shocks. Simulating the VAR model allows us to generate artificial time series for the two transition rates; we then use the steady state formula to obtain artificial times series for the unemployment rate. We compute the two hypothetical unemployment rates when alternatively one of the transition rates is fixed. It is then possible to calculate the beta coefficient where these simulated series conditional to the aggregate shocks replace their "actual" counterpart in Eqs. (9) and (10). As this exercise is not proposed in Fujita (2011), we redo the same calculations on US data by considering the same VAR model[23]. The contribution of the job finding rate to the unemployment volatility generated by aggregate shocks is 64% in France, close to the US case where it amounts to 58.5%.

If the French labor market was hit only by aggregate shocks that move unemployment and vacancies in the opposite direction, unemployment would be driven mainly by the fluctuations in the job finding rate. This result shows that the predominant role of the job finding rate comes from the labor market adjustment to traditional business cycle shocks. This seems close to the results obtained by Fujita (2011) on US data, although the job finding rate appears more important in France, as its impact is not delayed as in the US. This is all the more significant in that the aggregate shock contributes to almost half of the volatility of the French labor market flows.[24]

5. Conclusion

In France, both the job finding and separation rates contributed to unemployment fluctuations. In the last decade, the job finding rate played a dominant role in accounting for unemployment fluctuations. In our view, the sizeable contribution of the job finding rate is a salient feature of the French labor market. In the range of results found in the literature, France stands out as a country in which job finding influence on unemployment fluctuations is particularly dominant, especially in

[23] We have of course checked that we obtained the same IRFs as in Fujita (2011).

[24] We have computed the variance decomposition of transition rates and vacancies.

the recent years. Our analysis on French labor contract duality suggests that the rise in the use of short-term contracts could account for the rising contribution of job findings. These results are quite robust to the detrending method (HP filter or differentiation) and to the unemployment measure (steady state or actual). Moreover, another specificity of the French labor market lies in the dynamic relationship between transition rates and unemployment. This specificity confirms the leading role of the job finding rate in France. Unlike its US counterpart, the French separation rate does not lead fluctuations in unemployment and finding rates. The VAR analysis also shows that the separation rate is not very responsive to the aggregate shock, which tends to give less importance to job separations, hence more importance to job finding rates. In addition, job findings respond instantaneously to aggregate shocks, rather than in a delayed manner as in the US.

Overall, the French labor market seems to be characterized by specific transition rate dynamics. As the French labor market has much lower turnovers on average than most countries, and institutions such as unemployment insurance and employment protection are far more prevalent in France, does it mean that labor market institutions matter as much for cyclical adjustments as for equilibrium unemployment? Instead of giving a highly hypothetical answer at this stage, we favor the idea that more theoretical work must be done in the future on this issue.

Acknowledgments

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Appendix A. Worker flows in administrative data

In this appendix, we provide details on the administrative data (Fichier Historique). Job seekers registered at the Public Employment Service are classified in 5 different categories:

- Cat. A: looking and available for a job, and not working a single hour in the month.
- Cat. B: looking and available for a job, and working between 1 and 78 h in the month.
- Cat. C: looking and available for a job, and working over 78 h in the month.
- Cat. D: training.
- Cat. E (on-the-job search): looking for a job, but not available.

In this paper, we consider as unemployed a job-seeker in category A only. Petrongolo and Pissarides (2008) mixed in their analysis categories A and B. Our data also allows to observe whether new entrants in category A were working in the previous month or inactive. We also observe whether job-seekers exiting the registers take up a job or become inactive. When the origin of the new entrants (resp. the destination of the exiting job-seekers) is missing, we input it as a job separation (resp. a job finding). Thus we define a transition from unemployment to employment as:

- a transition from category A to categories B, C or E;
- and an exit from the registers (still category A) to take up a job.

We define a transition from employment to unemployment as:

- a entry into the registers (category A) following a job separation;
- and a transition from categories B, C or E to category A.

On average (1994–2010), 80% of total monthly outflows are transitions from unemployment (category A) to employment. 86.5% of total monthly inflows are transitions from employment to unemployment (category A). Finally, transitions from unemployment to inactivity are defined as transitions from category A to D and exit from the registers (category A) to inactivity. Transitions from inactivity to unemployment are defined as transitions from category D to A and entry into the registers (category A) from inactivity. The data does not provide any information on transition between employment and inactivity, which precludes a 3-state analysis.

Appendix B. Correcting for recall errors

Table 8 reports the estimates on recall errors. To assess the extent of our correction, we plot in Fig. 13 steady state unemployment rates before and after recall error correction. The correction of transition rates implies a higher unemployment rate because the relative correction on separation rates is larger than the one applied to finding rates. Finally, we do not correct for the difference between the levels of ILO and subjective unemployment. We argue that recall errors and the gap between subjective and ILO unemployment are separate issues. In addition, the survey does not provide

Table 8
Difference between contemporaneous outcomes and outcomes recalled with lags.

Recall lags (in months)	Unemployment rate	Separation	Finding
1	−0.0010	−0.0013	0.0013
	(0.585748)	(0.014647)	(0.716783)
2	−0.0025	−0.0014	−0.0009
	(0.193071)	(0.003103)	(0.748400)
3	−0.0043	−0.0019	−0.0050
	(0.021851)	(0.000011)	(0.103947)
4	−0.0055	−0.0025	−0.0069
	(0.003092)	(0.000000)	(0.036158)
5	−0.0059	−0.0029	−0.0024
	(0.000881)	(0.000000)	(0.458616)
6	−0.0071	−0.0023	−0.0088
	(0.000031)	(0.000001)	(0.003390)
7	−0.0078	−0.0028	−0.0056
	(0.000071)	(0.000000)	(0.127832)
8	−0.0086	−0.0036	−0.0103
	(0.000012)	(0.000000)	(0.004590)
9	−0.0086	−0.0041	−0.0100
	(0.000003)	(0.000000)	(0.001798)
10	−0.0083	−0.0047	−0.0107
	(0.000058)	(0.000000)	(0.000463)

LFS. Average computed for cohorts from January 2006 to December 2009. OLS estimates. Standard deviation in parenthesis.

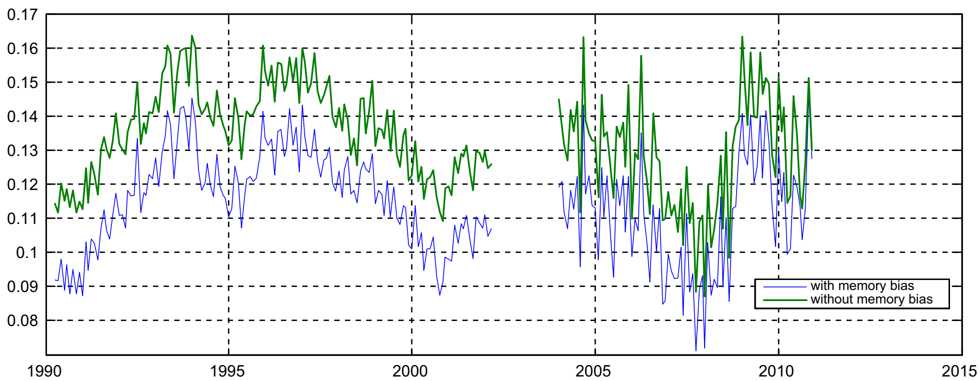

Fig. 13. Steady state unemployment.

Table 9
Impact of correction for recall error on the contribution of separation rates β^{EU} (finding rates β^{UE}, in parenthesis) to fluctuations in steady state unemployment.

Period	1990–2002	1994–2002	2004–2010
LFS			
1. HP	55.5 (44.6)	51.9 (48.1)	35.5 (64.5)
2. FOD	34.3 (65.7)	41.3 (58.5)	28 (72)
LFS no corr. for recall			
3. HP	62.7 (37.4)	62.4 (37.5)	40.9 (59)
4. FOD	47.8 (52.3)	50.5 (49.4)	35.7 (64.2)

LFS: LFS in the main text, after correcting for recall. LFS no corr. for recall: LFS without correction for recall. HP: HP filtering with smoothing 10^5. FOD: First-Order Difference.

information about past search activities. Finally, the cyclical properties of ILO and subjective unemployment rate are very similar (with a correlation of 0.98, see Appendix C).

Table 9 presents the contribution of separation rates to fluctuations in steady state unemployment using FH, LFS with and without the correction for recall error. It can be seen that β^{EU} is higher when LFS is not corrected for recall error. In our view, this is due to the larger relative correction on separation rates than on finding rates. Intuitively, the dominant effect is

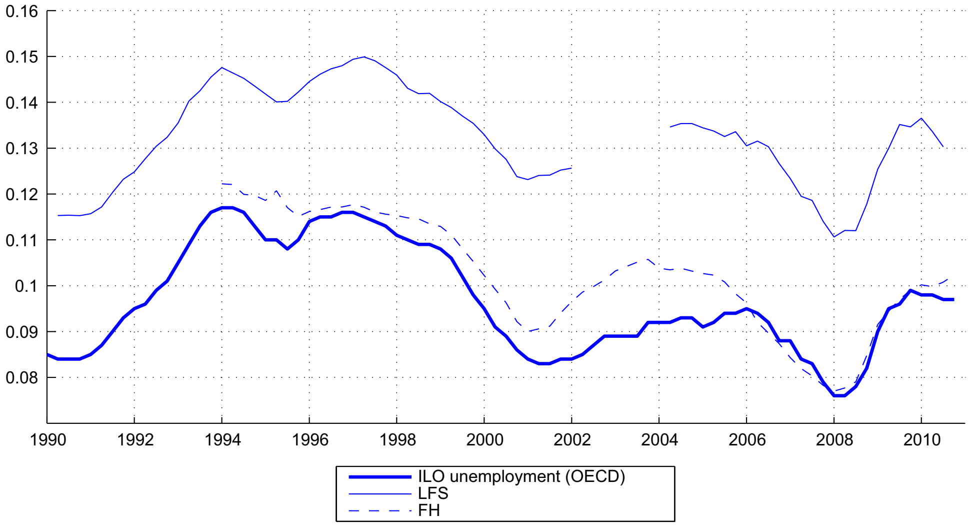

Fig. 14. Actual and ILO unemployment rates.

the following: uncorrected separation rates exhibit a much lower mean, implying larger deviations from the mean, hence a more significant contribution of separation volatility in the fluctuations of steady state unemployment.

Appendix C. Actual and ILO unemployment rates

Actual and ILO unemployment rates are shown in Fig. 14. The measure of the actual unemployment rate is consistent with the definition of unemployment specific to each dataset. In the retrospective calendar of the LFS, individuals self report their labor market status. In administrative data (FH), an individual is considered as unemployed if he is registered at the Public Employment Service. Those definitions of labor market status may differ from the official ILO classification. Moreover actual unemployment rates are computed using separation and job finding rates. Transitions with inactivity are not incorporated in actual U rates, while they contribute to the evolution of ILO unemployment. This is another potential source of difference. Fig. 14 shows that there is a shift in levels between actual unemployment rates and the ILO unemployment rate (the shift is greater for the actual unemployment rate derived from the retrospective calendar of the LFS). However the cyclical properties of the three unemployment rates are similar (correlation of 0.98).

Appendix D. The role of detrending method, exact decomposition versus counterfactual unemployment

Using US CPS data between 1967Q2 and 2010Q4, we compute the separation and job finding rates as in Fujita and Ramey (2009). Table 10 shows the β analysis of steady state unemployment relying both on Shimer (2012)'s counterfactual unemployment and Fujita and Ramey (2009)'s exact analysis (in columns) using different filtering methods to identify the business cycle component (HP filter with smoothing parameter 10^5 and 1600, First Order Difference).

There are very few differences in the contributions due to the decomposition approach, whether based on counterfactuals or exact decomposition (column (1) versus column (2)). However, the filtering method induces significant difference (lines 1–2 versus line 3). The main difference appears when we switch from HP filters to first difference. This difference is highlighted in the French case by Fig. 15.

Table 10
Impact of filtering and decomposition methods on the contribution of the separation rate (β^{EU}) and of the job finding rate (β^{UE}, in parenthesis).

	Counterfactual (1)	Exact decomposition (2)
1. HP filter, smoothing 10^5	35.0 (65.2)	35.0 (65.3)
2. HP filter, smoothing 1600	38.9 (61.3)	38.9 (61.3)
3. FOD	49.6 (50.7)	49.6 (50.7)

US CPS, 1967Q2–2010Q4. Counterfactual: based on hypothetical unemployment rates as in Shimer (2012). Exact Decomposition: of unemployment fluctuations as in Fujita and Ramey (2009).

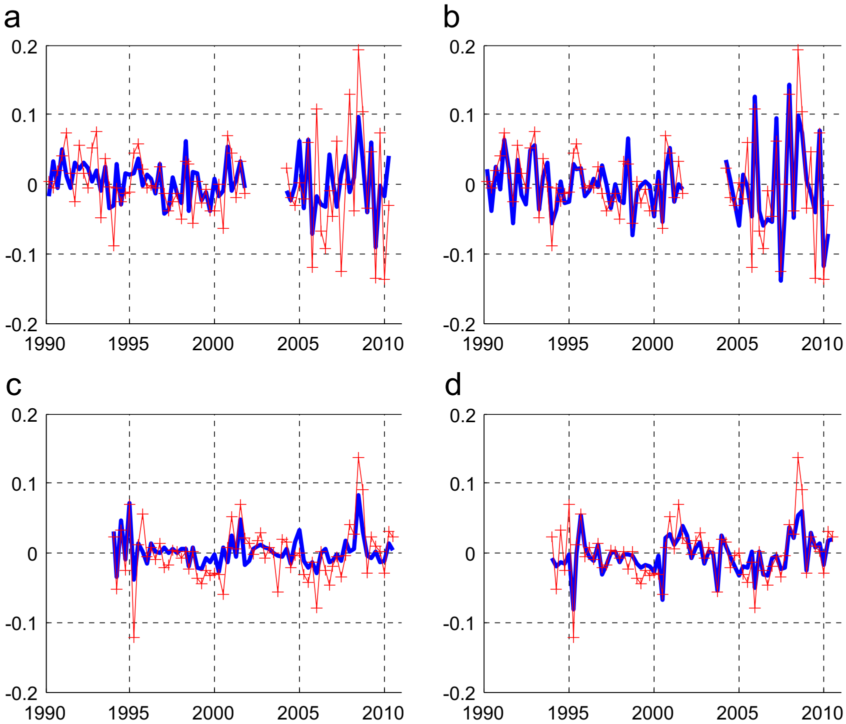

Fig. 15. Fluctuations in separations and job finding rates (bold line). Steady-state unemployment (+-). First-order difference. (a). LFS. Separation, (b). LFS. Finding, (c). FH. Separation, (d). FH. Finding.

Appendix E. Employment, unemployment and inactivity using LFS

In this appendix, we verify the robustness of our results when we take into account flows involving inactivity (defined as neither employed nor unemployed). As in Shimer (2012), we compute the six monthly gross flows between the 3 states, correct for recall error, seasonally adjust the time series,[25] correct for time aggregation, and compute quarterly averages. The contribution of changes in each transition rate to unemployment fluctuations is first computed as in Shimer's paper. It is based on hypothetical steady state unemployment rates predicted by fluctuations in only one transition rate, while the other 5 are set at their respective average levels. Fig. 16 shows the resulting time series, with the steady state unemployment rate plotted for comparison. Fig. 16 suggests that flows involving inactivity play little role in accounting for unemployment changes.

In order to quantify the importance of flows from/to inactivity in generating unemployment fluctuations, all times series are logged, then detrended using an HP filter with smoothing parameter 10^5 and first-order difference. βs are reported in columns (1) and (2) in Table 11.

Columns (1) and (2) in Table 11 indicate that, for each subperiod, unemployment fluctuations are mainly explained by transition to/from employment and unemployment. At business cycle frequency, changes in labor force participation have a minor impact on unemployment cyclical behavior. As in Shimer (2012), fluctuations in *EI* transition rate can actually reduce unemployment volatility. In addition, the comparison between the 2 sub-periods also suggests that the main result of the paper is robust: both rates equally contributed to unemployment fluctuations in the 1990s while, in the last decade, the *UE* transition rate played a leading role in accounting for the cyclical behavior of unemployment.

Smith (2011) proposes an alternative decomposition in a 3-state labor market. She summarizes the contribution of unemployment inflows s as the sum of direct transition ($E \rightarrow U$) and indirect transition through inactivity ($E \rightarrow I \rightarrow U$). Similarly, the outflow rate f is defined as the transition from U to E plus the transition through inactivity ($U \rightarrow I \rightarrow E$). Steady state unemployment equals $s_t/(s_t+f_t)$ with the extended definition of s_t and f_t mentioned above. This analysis then allows to disentangle the contribution of separation *EU* and finding *UE* rates from flows involving inactivity, while, at the same time, allowing to summarize the contribution of changes in separations s versus findings f in unemployment fluctuations. Results are reported in columns (3) and (4) in Table 11. Whether in column (3) or (4), separations s mainly occur through changes in direct transitions *EU* rather than flows through inactivity *EIU*. The same comment applies to findings. Finally, the comparison between columns (3) and (4) also suggests that the main result of the paper is robust: both separations s

[25] We proceed in this order as in Shimer's paper. We obtain the same results when seasonal adjustment is applied just prior to the decomposition analysis, after the quarterly averages. Results are available from the authors upon request.

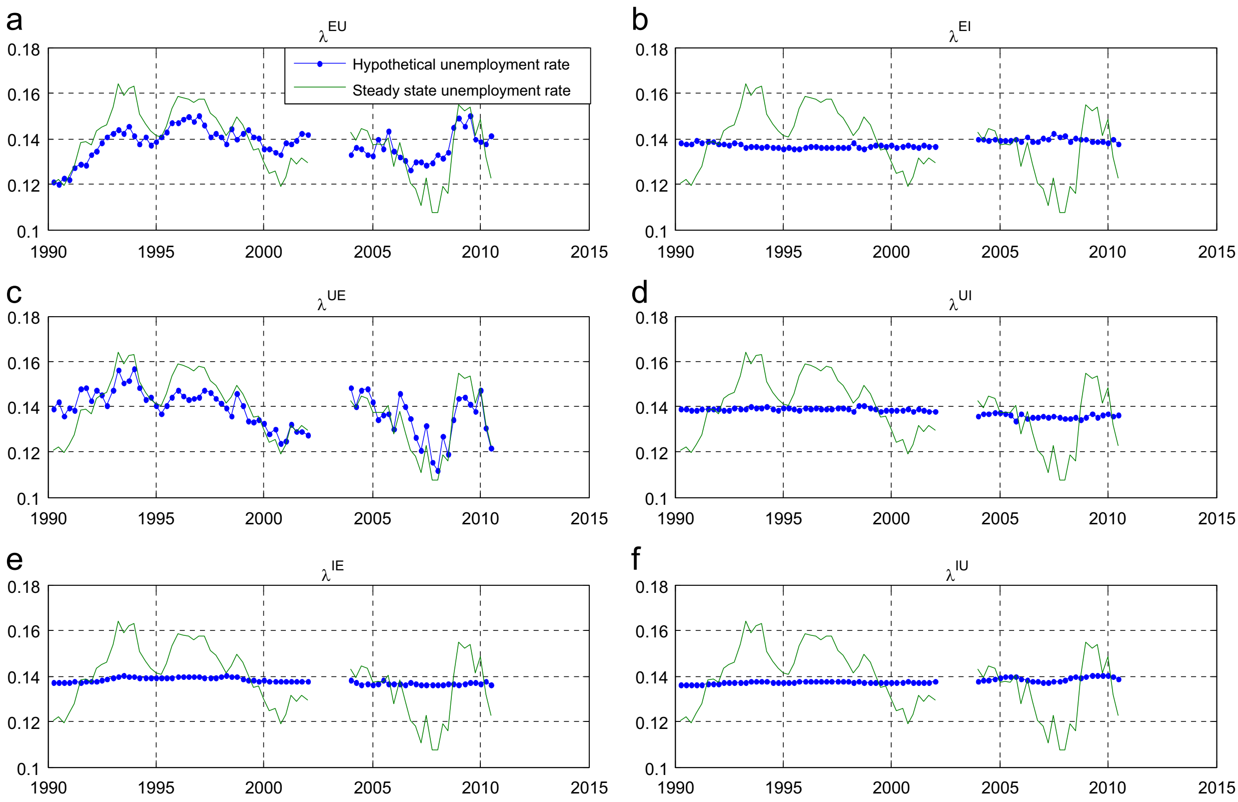

Fig. 16. LFS: Contributions of fluctuations in the instantaneous transition rates to fluctuations in the unemployment rate.

Table 11
LFS. Contributions to steady-state unemployment volatility. 3-state model.

Shimer (2012)				Smith (2011)			
		1990–2002 (1)	1994–2010 (2)			1990–2002 (3)	1994–2010 (4)
β^{EU}	HP	0.49564	0.31532	β^{s}	HP	0.53385	0.35135
	FOD	0.30971	0.23873		FOD	0.28718	0.27268
β^{UE}	HP	0.42428	0.62392	β^{f}	HP	0.459827	0.661701
	FOD	0.68559	0.78532		FOD	0.70287	0.74086
β^{EI}	HP	−0.033308	−0.025803	β^{EU}	HP	0.49573	0.31537
	FOD	−0.017656	0.029075		FOD	0.30976	0.23876
β^{UI}	HP	0.019333	0.019055	β^{EIU}	HP	0.038121	0.035973
	FOD	0.017881	−0.047652		FOD	−0.02258	0.033911
β^{IE}	HP	0.064558	0.019015	β^{UE}	HP	0.42427	0.6239
	FOD	−0.0097407	−0.0040648		FOD	0.68557	0.78529
β^{IU}	HP	0.031201	0.050248	β^{UIE}	HP	0.035557	0.037801
	FOD	0.0072193	0.013812		FOD	0.0173	−0.044434
$\sum\beta$	HP	1.0017	1.0018	$\sum\beta$	HP	0.99367	1.013
	FOD	0.993	1.0152		FOD	0.99005	1.0135

and findings *f* equally contributed to unemployment fluctuations in the 1990s while, in the last decade, unemployment exits played a leading role in accounting for the cyclical behavior of unemployment. Smith (2011)'s analysis shows that this result is driven by changes in the contribution of direct transitions *EU* and *UE*, rather than flows through inactivity *EIU* and *UIE* whose contribution remains stable across sub-periods.

Appendix F. Cross-correlations between unemployment rate and transition rates

Figs. 17 and 18 display the cross-correlations at various leads and lags between fluctuations in job separation and job finding rates and steady state unemployment. We consider both HP filtering and first differencing for LFS (Fig. 17) and FH (Fig. 18).

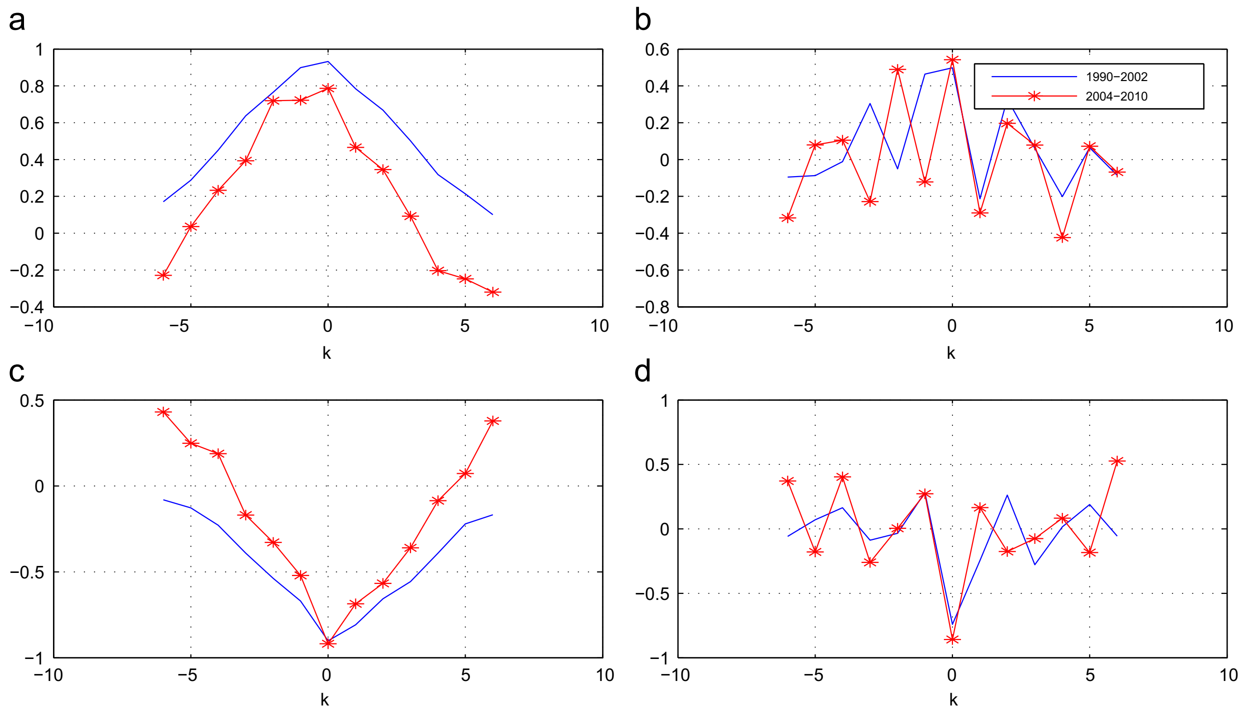

Fig. 17. LFS: Cross-correlations between fluctuations in job separation and job finding rates and steady state unemployment. (a) and (b): Cross-correlations between fluctuations in unemployment at time t and job separation rate at time $t+k$. ((a) HP filter; (b) first order difference). (c) and (d): Cross-correlations between fluctuations in unemployment at time t and job finding rate at time $t+k$. ((c) HP filter; (d) first order difference).

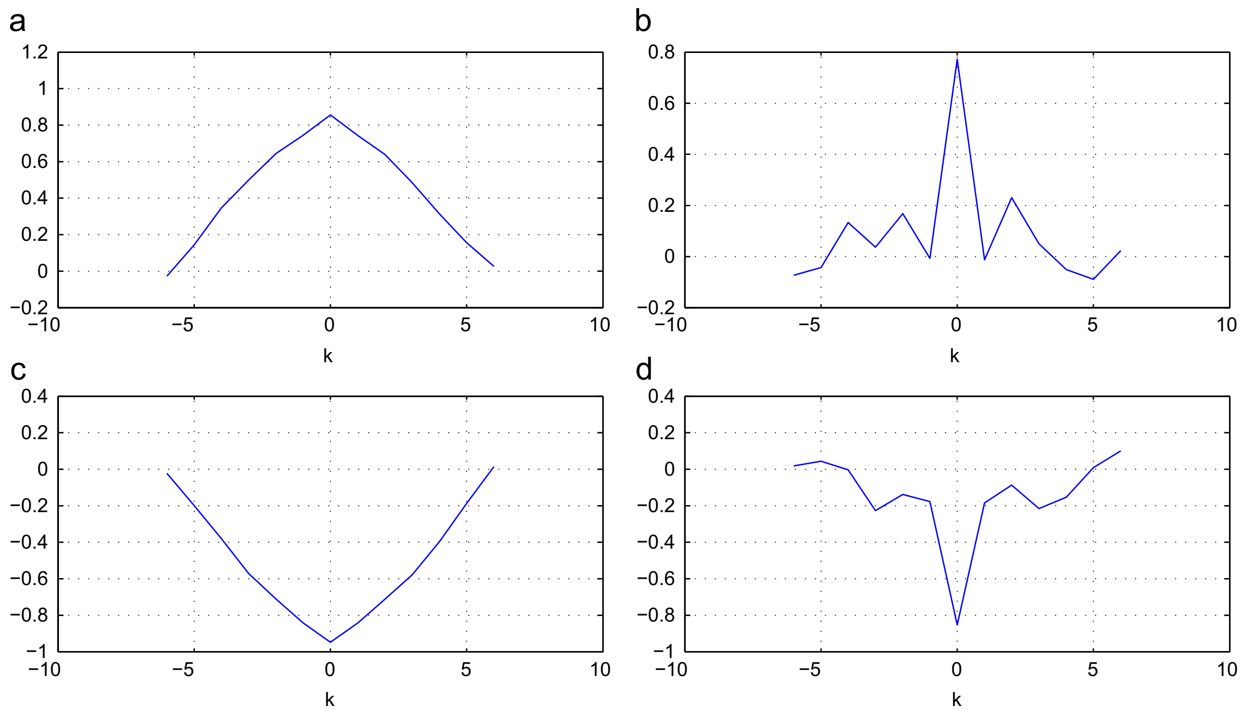

Fig. 18. FH: Cross-correlations between fluctuations in job separation and job finding rates and steady state unemployment. (a) and (b): Cross-correlations between fluctuations in unemployment at time t and job separation rate at time $t+k$. ((a) HP filter; (b) First Order Difference). (c) and (d): Cross-correlations between fluctuations in unemployment at time t and job finding rate at time $t+k$. ((c) HP filter; (d) First Order Difference).

Appendix G. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.euroecorev.2015.01.013.

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