French Unemployment Dynamics: a Three-State Approach

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Abstract

In this paper, we provide a new assessment of labor market flows in France over the period 2003-2012. By using the French Labour Force Survey and the ILO's standards, we construct gross worker flows and transition rates between the three main labor market states: employment, unemployment and inactivity. The cyclical properties of the series suggest that flows jointly involving employment and unemployment are the most sensitive to economic conditions. Flows between participation and non-participation exhibit less cyclical patterns over the business cycle. We then decompose unemployment rate fluctuations by applying the steady state and the non-steady state decomposition. With a three state view of labor market, we find that the job finding rate is the first driver of unemployment fluctuations in France, while the job separation rate is the second. This decomposition also demonstrates that the role of inactivity in shaping unemployment is not negligible, justifying a complete analysis with three labor market states. In addition, we also propose an analysis based on three partitions of the overall French population. In this framework, the dynamic decompositions indicate that the sources of unemployment are different among sub-groups, in particular for women, old workers, unskilled and skilled workers.

Keywords: Transition rates, gross worker flows, unemployment dynamics
JEL classifications: J60, E24, E32

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1 Introduction

How do labor market flows shape French unemployment dynamics ? Do inflows or outflows from unemployment drive unemployment fluctuations ? What is the role of flows implying inactivity in this mechanism ? Answers to these questions are crucial to understand unemployment dynamics. From researchers point of view, they are naturally connected with the search and matching framework (Mortensen and Pissarides (1994)) and they help to improve calibration of theoretical models. Furthermore, depending on the unemployment driving forces, they lead the choice of policies to reduce the rise in unemployment during economic downturns.

In a first step, this paper aims to construct worker flows in France. By using the French Labour Force Survey (FLFS, henceforth), we propose a new assessment of labor market flows based on the definitions of International Labour Organization (ILO, henceforth). The FLFS allows to compute, over the period 2003-2012, flows between the three main labor market states: employment, unemployment and inactivity. The consideration of inactivity gives a complete picture of labor market dynamics. However, due to the rotating property of FLFS samples, worker flows and transition rates associated are not directly useful because they may be biased. To avoid this problem we propose a new longitudinal weight, which calibrates each longitudinal sample structure with population structure for some important variables. Gross worker flows series are not available in France, so their constructions is crucial.

In a second step, we document the main stylized facts about French unemployment dynamics. Flows series suggest that the job separation to unemployment and the job finding account for a large part of unemployment dynamics in France. Since the recession of 2008, the job separation gross flow has remained high, while, the job finding gross flow has regained its pre-crisis level. However, in terms of transition rates, the job finding rate has remained low. When we focus on the series cyclical properties, we find that job separations (gross flow and transition rate) are highly counter-cyclical. The job finding rate is clearly pro-cyclical. Both rates seem to adjust contemporaneously with business cycle. The cyclical patterns of the job finding gross flow are less obvious. Flows between participation and non-participation are less sensitive and do not react contemporaneously with business cycle.

In a third step, with a "three-state" view of labor market, we disentangle the role of each flow in shaping French unemployment dynamics. Several studies assess the relative contributions of transition rates by assuming that the steady state unemployment is a good approximation for current unemployment rate. We argue that this assumption is not necessarily verified for the French economy because transition rates are relatively low (comparatively to U.S.). In this sense, and in order to capture the sluggishness of French labor market, a decomposition which allows deviations of current unemployment from its steady state counterpart appears more appropriate. To address this issue, we adopt a mixed approach and we apply both, the classical steady state and the dynamic non-steady state decomposition. We demonstrate that the job finding rate has a dominant influence, since it generates 50% of unemployment variations. The job separation rate contributes to 23% of French unemployment fluctuations. Transitions implying inactivity are not negligible and account for 26% of unemployment fluctuations. These findings are relevant to justify the consideration of inactivity to the analysis. Our decompositions suggest that to understand the French unemployment, it is crucial to focus on the outflows process from unemployment.

In addition to the study of French labor market at the aggregate level, we also propose an analysis across sub-groups. The analysis based on the overall population presupposes that all workers are homogenous. We claim that this assumption can hide important discrepancies between sub-groups. To avoid this limit, we divide the overall population according to three variables: gender, age and education level. We show that unemployment rate of women is more relied on the outflow process than what it is for their male counterparts. There is no structural differences in the impact of flows between inactivity and labor force in shaping male and female unemployment fluctuations. Young workers are much more likely to move on the labor market, and their unemployment rate is explained mainly by the job finding. In contrast, flows between participation and non-participation play a dominant role in the changes that occur for unemployment of older people. A focus on the level of education suggest that the higher the level of education is, the lesser the job separation rate shapes unemployment. Surprisingly, flows between participation and non-participation explain a large proportion of skilled unemployment fluctuations.

These issues about the unemployment driving forces are largely documented for the U.S. labor market. However, the debate remains active in the literature. In their pioneer contributions Blanchard and Diamond (1990) and Davis and Haltiwanger (1992) conclude that unemployment fluctuations are mainly caused by job separations. These studies give a strong empirical basis, used by Mortensen and

Pissarides (1994), to construct the first matching model with endogenous job destruction. Recently, Hall (2005) and Shimer (2012) claim that the job separation rate has only a minor influence in explaining unemployment fluctuations. Unemployment dynamics are, according to them, mainly explained by the job finding rate. Based on these results, several theoretical studies assume that the job separation is constant and acyclical (Blanchard and Gali (2010), Gertler and Trigari (2009)). However, other recent empirical studies (Fujita and Ramey (2009), Elsby et al. (2009)) challenge Shimer's results, and demonstrate that both the job separation rate and the job finding rate are useful to understand unemployment dynamics.

Due to data limitations, the French case is relatively understudied. With a "two-state" view of labor market, Petrongolo and Pissarides (2008) and Elsby et al. (2013) analyze the French labor market in comparative studies. On the one hand, Petrongolo and Pissarides (2008) indicate that the job finding rate explains 80% of unemployment variations, while, on the other hand, Elsby et al. (2013) argue that both job separation and job finding are determinant (50:50 job separation/finding split). Hairault et al. (2015) provide new evidences by studying exclusively the French labor market. They show that the role of job separation in shaping unemployment has changed during the last recession. If both rates explain unemployment fluctuations during the 1990 decade, the job finding rate is the first determinant of French unemployment during the 2000 decade. Conclusions of these three studies do not converge and French unemployment dynamics remain opaque. This justifies new studies as the one provided here. Furthermore, by using administrative data or a retrospective calendar to compute worker flows, the definition of unemployment spells is not based on international standards and so their results may be biased. Moreover, none of the three papers aforementioned pays much attention to the role of inactivity in driving unemployment fluctuations. In this paper, we avoid these drawbacks by using the longitudinal samples of FLFS.

The remainder of this paper is organized as follows. Section 2 gives the main elements to understand series construction. Section 3 documents the main stylized facts of labor market flows in France. Section 4 studies the cyclical properties of the series. In section 5 we quantify the contribution of each flow in aggregate unemployment fluctuations. In this section, we use both the steady state and the dynamic decomposition. In section 6, we relax the homogeneity hypothesis by dividing the overall population into several sub-groups. We also replicate the dynamic decomposition on these sub-groups. Finally, section 7 concludes.

2 Measuring gross worker flows

2.1 Data

To construct gross worker flows on the labor market, we use the French Labour Force Survey (FLFS henceforth) on the period 2003-2012. At the end of 2012, the size of the survey sample is 60000 households. The FLFS's sample is a rotating panel in which each household is interviewed six times, once each quarter[1]. The sample is divided into six waves. Every quarter one sixth of the sample is renewed, one wave leaves the sample while a new wave integrates it. The survey gives a set of informations about individuals' characteristics (gender, age, qualification etc.), but its main advantage is the individual labor market state classification according to the International Labour Office definitions (ILO). An individual is classified into three states: employed (E), unemployed (U) and inactive (I). We construct labor market flows by matching workers between two consecutive quarters. Nonetheless, this match is not perfect. Between two consecutive surveys the incompressible loss, consequence of the panel structure of the sample, is one sixth of the sample size. To this first loss, we have to add the non-response. The non-response phenomena is problematic because it introduces a bias in the estimation. On average, 80% of the individual are common between two consecutive surveys. To reduce the non-response bias and the sample fluctuations, we reweight the part of the common sample between two surveys with a calibration. The purpose of this step is to equalize the longitudinal sample structure with the population structure in period t for some important variables. Moreover, if calibration variables are relevant, an unique step of calibration can reduce the non-response bias. The technical details about the calibration and the calculation of the new weight are provided in appendix A.

By using the quarterly FLFS we construct worker flows according to the ILO standards. These definitions are an important advantage to distinguish active worker from inactive worker. Hairault et al. (2015) also use the FLFS, but, they compute the flows from the retrospective calendar. In this calendar each individual recalls his labor market position during the last eleven months before the first interview. This information provides relatively long series of worker flows, since

[1]Before 2003, the FLFS had an annual frequency

the retrospective calendar is available since 1990. However, the use of the retrospective calendar has three major drawbacks. Firstly, the redesign of FLFS implies a break in the series between 2002 and 2004. Secondly, the concepts of employed, unemployed and inactive are based on individual declarations. By this way, the unemployed concept is close to the census unemployment concept. If an individual can distinguish easily the employment spells and the "non-employment" spells, he has more difficulties to differentiate unemployment spells with inactivity. This can be problematic to construct worker flows between these two states. Thirdly, the retrospective calendar is biased by recall errors. Several studies establish that individuals under-reported unemployment spells. This under-estimation is not necessary voluntary, but after a long time there is a psychological effect that induces omission of "negative" spells. Hairault et al. (2015) propose an original strategy to correct for recall error bias. Nonetheless, they can not overcome the second problem while we do by using the ILO's standards. Furthermore, the fact that ILO's definitions are in line with international standard is an advandage, since it allows comparison with other international studies which often use these concepts.

2.2 Definition

2.2.1 Fundamental equations

Three states are considered on the labor market: employment (E), unemployment (U) and inactivity (I). Gross worker flows are denoted by two consecutive capital letters. The first one is the origin of the flow, the second one its destination. Quarterly transition rates p^{AB} are the number of individuals who move from the state $A \in \{E, U, I\}$ to the state $B \in \{E, U, I\}$ between t and $t+1$ divided by the stock of state A in period t. For instance, the separation rate to unemployment is:

$$p_t^{EU} = \frac{EU_{t,t+1}}{E_t} \tag{1}$$

This transition rate mirrors the probability that an employed worker in period t looses his job to be unemployed in $t+1$. This interpretation implies two implicit assumptions. Firstly, we assume that transition rates are constant during the period $\{t, t+1\}$. Secondly, we suppose that on average all employed workers have the same probability to loose their job and to become unemployed. The logic is the same for the other transition rates. Gross worker flows and transition rates series are seasonally adjusted by x12 arima process.

Stocks dynamics depend on gross flow evolutions. For example, unemployment dynamics are related to inflows and outflows of unemployment, and evolve according to the following law of motion:

$$\Delta U_{t+1} = U_{t+1} - U_t = EU_{t,t+1} + IU_{t,t+1} - UE_{t,t+1} - UI_{t,t+1} \tag{2}$$

Unemployment decreases when outflows exceed inflows. This decrease can be the result of two mechanisms: a rise in job finding or an increase of outflows from unemployment to inactivity. Equation (2) demonstrates that a diminution of unemployment does not mean necessarily that the conditions for access to employment have improved. In contrast, a rise in unemployment is not systematically the sign of an increase in job separation. If during a period more inactive workers begin to search for a job, unemployment stock increases. In order to assess the role of inactivity in the unemployment evolutions, one has to use a model with three labor market states.

By rearranging (2), we can express the law of motion for unemployment as a function of the transition rates:

$$\Delta U_{t+1} = p_t^{EU} E_t + p_t^{IU} I_t - (p_t^{UE} + p_t^{UI}) U_t \tag{3}$$

Similarly, we can write the law of motion for employment or inativity. Notice that the recent literature focuses on transition rates (Shimer (2012), Fujita and Ramey (2009), Hairault et al. (2015)). The studies dealing with gross worker flows are older (Blanchard and Diamond (1990)). In this article, we pay attention, when it is possible, to both gross flows and transition rates in order to provide a complete picture of French labor market dynamics.

2.2.2 Temporal aggregation bias

The FLFS gives individual labor market positions with a quarterly frequency. This discrete time representation of labor market dynamics can miss important worker flows. In discrete time all the infra-period transitions are not taken into account. The problem is that, within a quarter an individual can make multiple transitions and the FLFS matching will catch at most one. So, transition rates as in (1) suffer from “temporal aggregation bias” because they under-estimate mechanically the level of flows. Consequently, we correct the transition rates series of temporal aggregation bias by applying the Shimer’s pioneering method, and compute the instantaneous transition rates λ_t^{AB}. To apply this correction, we model a continuous time representation of labor market transitions.

3 Labor market flows in France

In this section, we present the most interesting stylized facts obtained by the FLFS's data. We study the evolution of gross worker flows and transition rates over the last decade.

Figure 1 displays the evolution of the three main labor market indicators over the last ten years. The French unemployment rate is characterized by a trend break beginning with the recession of 2008. Between 2006 and 2008, the unemployment rate decreases by two percentage points. Since 2008, the unemployment rate has continuously increased until it approached 10% at the end of 2012. The activity rate and the employment rate have been relatively constant over the last decade. This first analysis shows that unemployment is more sensitive to economic fluctuations than the two other indicators.

	Gross Flows			Transition rates		
From... ...To	E	U	I	E	U	I
E	–	544	437	–	22,35	3,68
U	452	–	458	1,79	–	3,86
I	521	400	–	2,06	16,48	–

Table 1: Average transition matrix
Source: FLFS (2003-2012). Working-age population between 15 and 64 years old.
Note: Worker flows are expressed in thousand, transition rates are expressed in percentage.

Table 1 displays the average gross worker flows and transition rates on the period 2003-2012. Each quarter, 544 thousand workers return to job while 452 thousand are separated from their job and become unemployed. The first destination when a worker leaves his job is the inactivity state. Furthermore, it appears that gross flows between participation and non-participation are high. Approximately 50% of these transitions imply flows between the two states of "non-employment". On average, 7% of the working-age population change labor market state per quarter. Focusing on transition rates, the probabilities to separate from or to find a job are relatively low. Moreover, the probability to leave

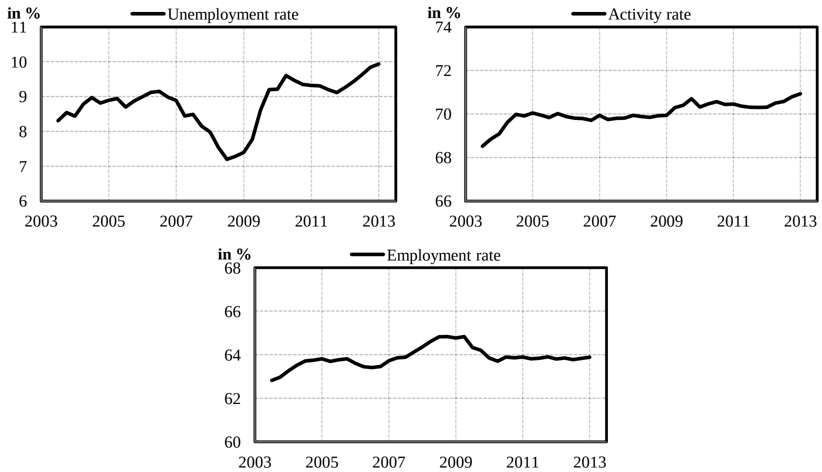

Figure 1: Labor market stocks in France
Source: FLFS (2003-2012). Working-age population between 15 and 64 years old. Series are seasonally adjusted with x12 ARIMA process

the inactivity state is weak.

Figures 2 and 3 plot gross worker flows and transition rates evolutions over the 2003-2012 period. In each graph, periods of recession are depicted by shaded areas[2]. The job separation gross flows EU increased significantly in 2008. In the last quarter of 2007, 380 thousand workers separated from their job and became unemployed. One year later, 520 thousand workers have lost or quit their job. The 2008 recession is characterized by a sudden and persistent increase in job separations. Since 2009, there has been 480 thousand job separations on quarterly average. Before 2008 on average, job separations amounted to 430 thousand. The same cyclical features are perceptible for the job separation transition rate. From the 2008 recession, the level of job separations has remained persistently high. Both gross flows and transition rates EU seem to be counter-cyclical.

Gross worker flows from unemployment to employment UE exhibit another cyclical feature. During the recession, job finding sharply decreased. In the third quarter of 2007, 590 thousand unemployed workers found a new job. Two quarters later, only 490 thousand unemployed workers returned to employment. However, the decrease in job finding was not persistent. From 2009, the level of job finding gross flow has been rising again, and it has recovered its pre-recession level. While job separations gross flow have remained high since 2009, job finding gross

[2] The French National Institute of Statistics and Economic Studies defines recessions as period of two consecutive quarters of decline in real GDP.

flow have regained its pre-recession level. However, the cyclical path of the job finding rate is different from its gross flow counterpart. The job finding rate p^{UE} increased before 2008 but the beginning of the recession reduced it by five percentage points. The probability for an unemployed worker to find a new job drops sharply in recession. This means that the job finding rate is pro-cyclical. Notice that the transition rate and the job finding gross flow do not have the same cyclical pattern. Firstly, the job finding rate appears to be pro-cyclical, while, the cyclical feature of job finding gross flow seems more ambiguous. Secondly, in contrast to the job finding gross flow, the decrease in the job finding rate, since 2008, was persistent.

Gross flows jointly involving unemployment and inactivity show an interesting feature. One year after the recession, more unemployed workers stopped searching for a job and, in the same time, more inactive workers started searching actively for a new job. The first phenomenon can be interpreted as the "discouraged worker effect". The second one can be seen like an "added-worker effect". Transition rates p^{IU} and p^{UI} are less sensitive to business cycle. Globally, gross flows and transition rates between participation and non-participation are less sensitive to economic conditions.

This preliminary analysis leads to two mains results. Firstly, flows and transition rates between employment and unemployment are the most sensitive series. Secondly, within these transitions, it seems that the level of the job finding rate has decreased significantly after the Great Recession. In the next section, we study in more details the cyclical properties of the series.

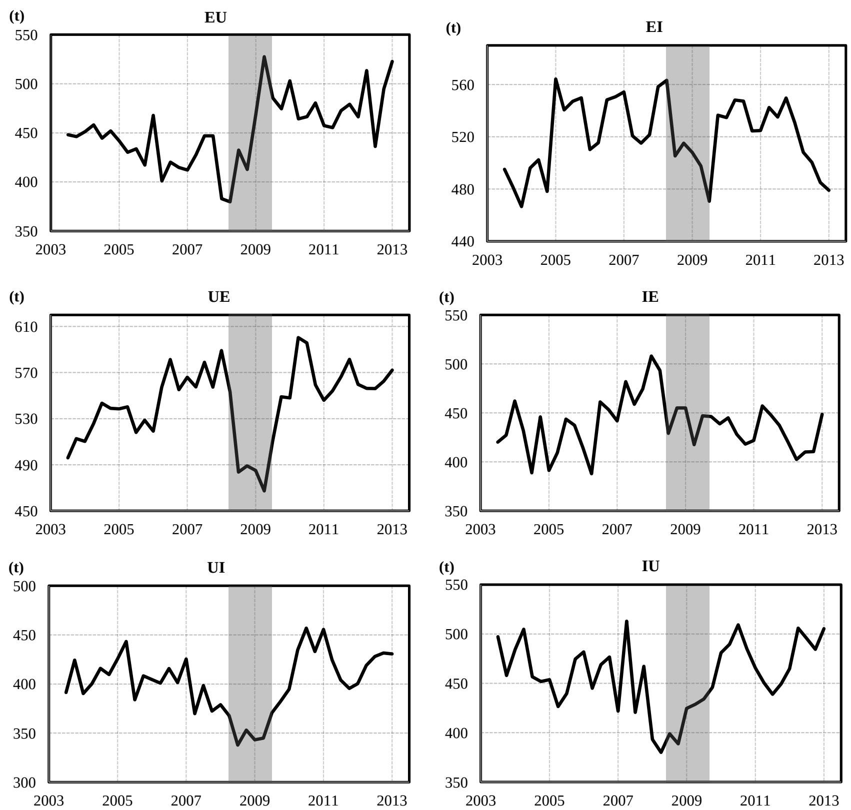

Figure 2: Gross worker flows in France.
Source: FLFS (2003-2012), author's calculations. Working-age population between 15 and 64 years old. Series are seasonally adjusted with x12 ARIMA process. *Note*: Gross worker flows are expressed in thousand (t), shaded areas indicate period of recession.

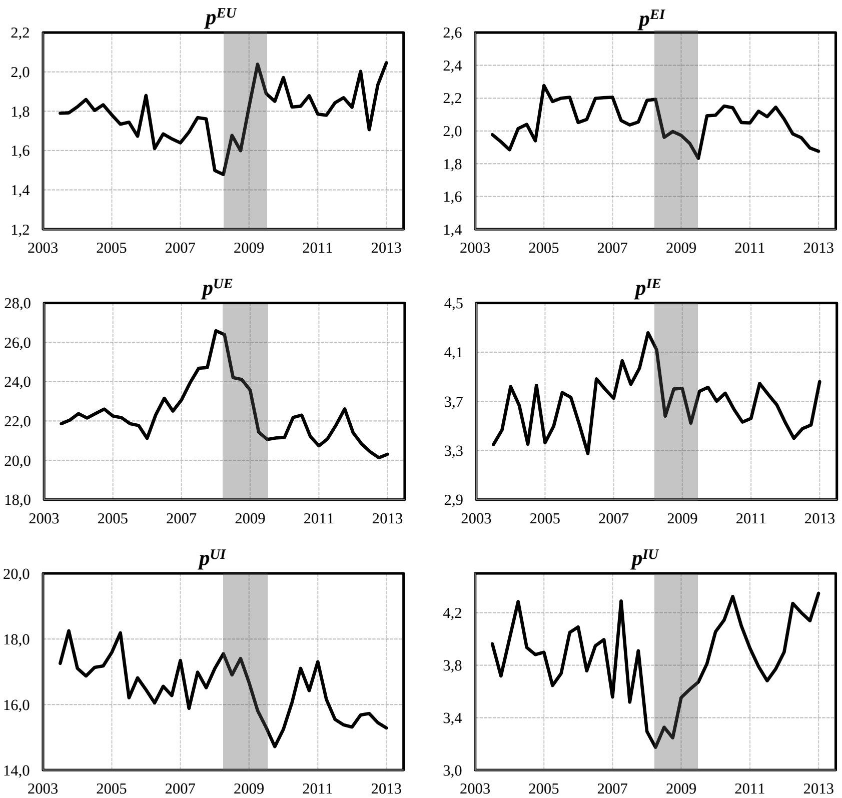

Figure 3: Transition rates in France.
Source: FLFS (2003-2012), author's calculations. Working-age population between 15 and 64 years old. Series are seasonally adjusted with x12 ARIMA process. *Note*: Transition rates are expressed in percentage (t), shaded areas indicate period of recession.

4 Cyclical properties of flows

The goal of this section is to shed light on the cyclical properties of gross worker flows and transition rates. As Fujita and Ramey (2009) we compute correlations between an indicator of economic activity and flows for some leads and lags. We use the aggregate productivity as a proxy for business cycle. The latter is defined as the real GDP divided by the number of employed workers. The trend components of the series are extracted by a Hodrick-Prescott (HP henceforth) filter with standard smoothing parameter. The transition rate series are adjusted for time aggregation error.

Figure 4 displays cross correlations between aggregate productivity and transition rates for lags from -3 to +3. The job separation rate p^{EU} is clearly countercyclical. This cyclical property means that during recessions the probability to

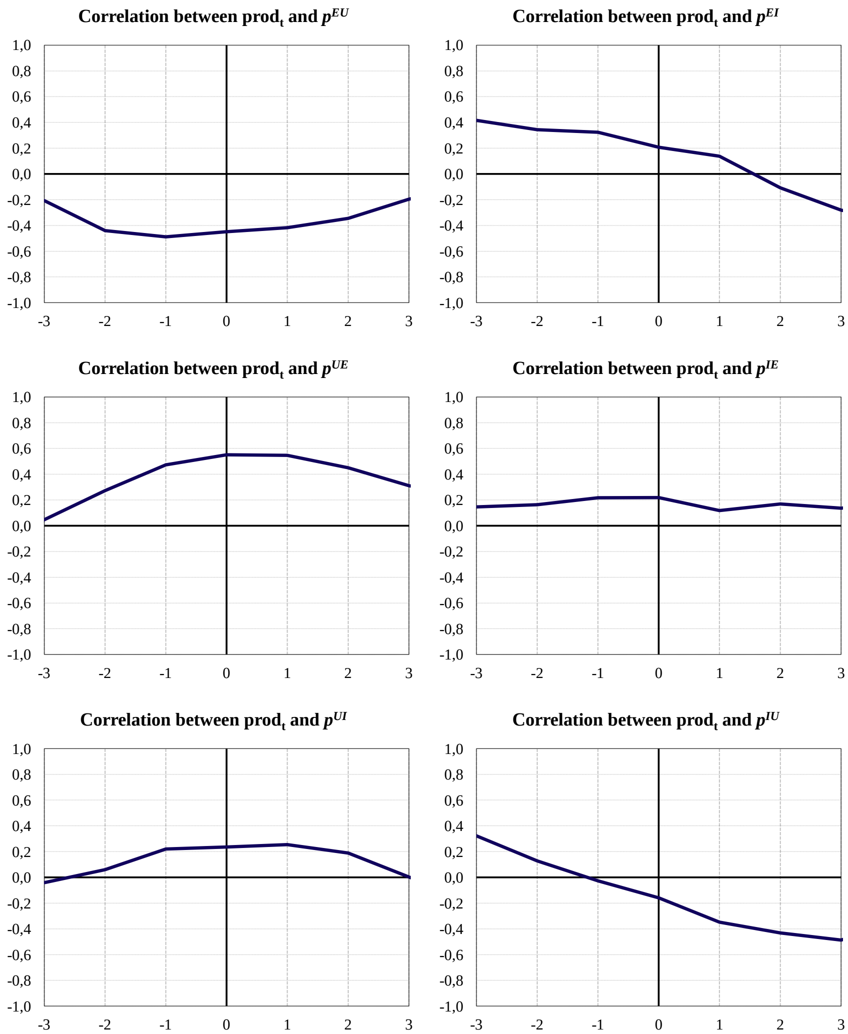

Figure 4: Cross correlation between aggregate productivity and transition rates. Source:FLFS (2003-2012), author's own calculations. Transition rate series are adjusted for time aggregation error. Series are detrended with HP filter with standard smoothing parameter $\lambda = 1600$.

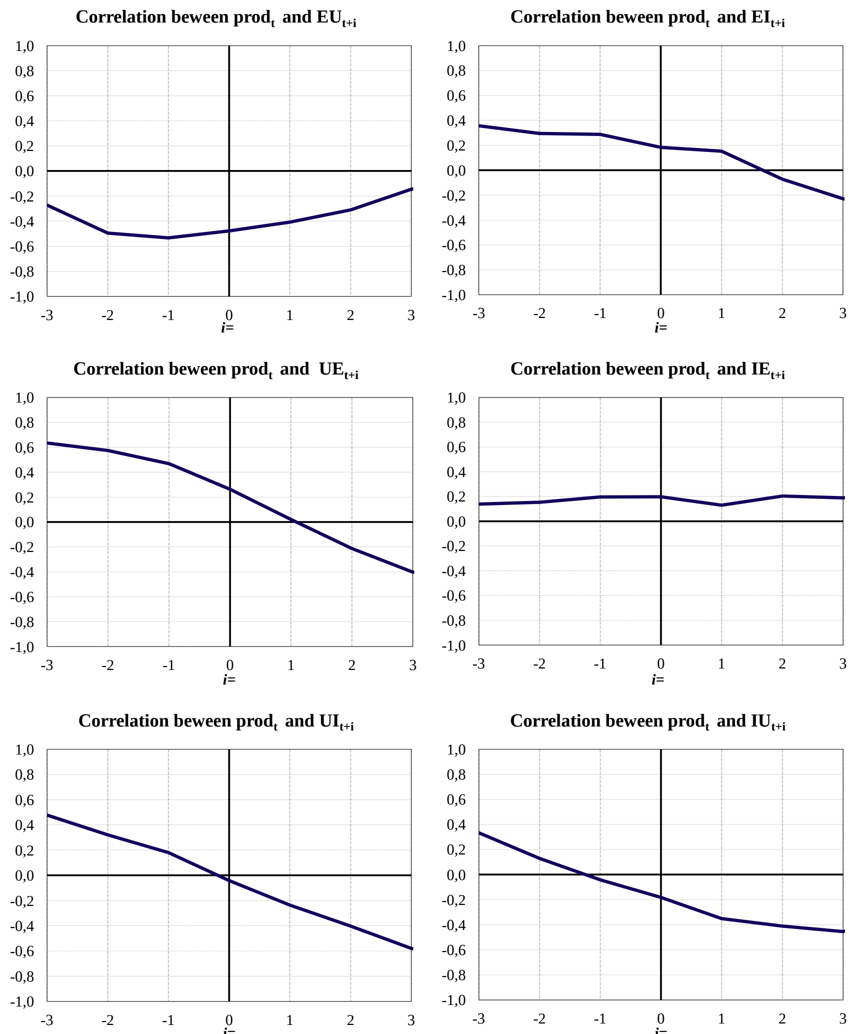

Figure 5: Cross correlation between aggregate productivity and gross worker flows. Source:FLFS (2003-2012), author's own calculations. Series are detrended with HP filter with standard smoothing parameter $\lambda = 1600$.

	Baker (1992)
p^{EU}	0,33
p^{EI}	0,12
p^{UE}	-0,55
p^{IE}	-0,27
p^{UI}	-0,13
p^{IU}	0,79
$\Rightarrow E$	0,08
$E \Rightarrow$	0,11
$\Rightarrow U$	0,47
$U \Rightarrow$	0,61
$\Rightarrow I$	0,37
$I \Rightarrow$	0,17

Table 2: Cyclical properties of transition rates
The cyclicality of the series is the coefficient on unemployment rate in the regressions. The sample is between 2003-1 and 2012:3.
*Significant levels, 1%:***, 5%:**, 10%:**

move from employment to unemployed is higher. Concerning the job finding rate p^{UE} it is the opposite. During recessions, the opportunities to find a new job are less important for unemployed workers. The job finding rate is pro-cyclical and moves contemporaneously with the cycle. Others transitions rates show less cyclical properties because their contemporaneous correlation coefficients are weak. Transition rates p^{EI}, p^{IE} and p^{UI} are moderately pro-cyclical, while, p^{IU} is moderately counter-cyclical.

In figure 5 we repeat the same exercise for gross worker flows. Job separation gross flow is counter-cyclical. More employed workers loose or quit their job during economic downturns. The second plot of the first column reveals that the cyclical characteristics of job finding gross flow are less obvious. It seems that job finding gross flow is contemporaneously pro-cyclical. However, this cyclical pattern is not verified for two leads, since the correlation between UE and aggregate productivity is negative. Some quarters after the recession job finding (re)increase. Gross worker flows jointly involving employment and inactivity are less correlated with business cycle. Gross worker flows UI and IU do not adjust contemporaneously with the cycle. Their correlations with aggregate productivity are negative and higher for two leads. Some quarters after the recession, worker flows between the two "non-employment" states escalate.

The table 9 in appendix B indicates that the results are not sensitive to the use of a higher smoothing parameter in the HP filter. However, and naturally, when a first order difference (FOD henceforth) filter is used, the level of correlation coefficients is reduced. The poor properties of the FOD filter may explain this phenomenon.

To assess the robustness of the previous results as regard to the choice of business cycle proxy, we follow the same approach as Baker (1992) and Gomes (2012). We estimate by an ordinary least square regression the cyclical properties of the log of transition rates on a trend, season dummy and unemployment rate. The estimation results are depicted in Table 2. The regressions confirm the counter-cyclicality of the job separation rate and the pro-cyclicality of the job finding rate. However, they suggest that p^{EI} and p^{UI} are acyclic because their regression coefficients are not significant. According to these regression, p^{IE} is pro-cyclical and p^{IU} is counter-cyclical. The second part of Table 2 provides the results of regressions with entries ans exits of each state as dependent variables. All entries and exits of each state are counter-cyclical. This finding suggest that economic downturns are periods favorable to adjustments in the labor market.

The analysis of this section reveals that flows involving employment and unemployment are highly correlated with the business cycle. Transitions rates p^{EU} and p^{UE} seem to adjust contemporaneously with the cycle. Flows between labor force and non-participation are broadly less cyclical. In the next section we aim to quantify the role of each flow in unemployment variability.

5 Decomposing unemployment fluctuations

The two previous sections give the first useful elements to understand French labor market dynamics over the last decade. The purpose of this section is more ambitious. It will deal with quantify the contributions of transition rates to unemployment variations. Several studies (Shimer (2012), Fujita and Ramey (2009), Elsby et al. (2009), etc.) measure these contributions by assuming that steady state unemployment is a good approximation for actual unemployment. Nonetheless, due to low transition rates on the French labor market, there are some reasons to hesitate in applying only the steady state decomposition. In this section we address this issue by applying both the steady state and the non-steady state decomposition.

5.1 The steady state approach

With the three states view of labor market, we can write stock dynamics as:

$$\Delta E_{t+1} = \lambda_t^{UE} U_t + \lambda_t^{IE} I_t - \left(\lambda_t^{EU} + \lambda_t^{EI}\right) E_t$$

$$\Delta U_{t+1} = \lambda_t^{EU} U_t + \lambda_t^{IU} I_t - \left(\lambda_t^{UE} + \lambda_t^{UI}\right) U_t$$

$$\Delta I_{t+1} = \lambda_t^{EI} E_t + \lambda_t^{UI} U_t - \left(\lambda_t^{IE} + \lambda_t^{IU}\right) I_t$$

In equilibrium $\Delta E_{t+1} = \Delta U_{t+1} = 0$, by rearranging these equations we express steady state unemployment as a function of all the transition rates:

$$u_t^* = \frac{\lambda_t^{EU} + \frac{\lambda_t^{IU}}{\lambda_t^{IU} + \lambda_t^{IE}} \lambda_t^{EI}}{\lambda_t^{EU} + \frac{\lambda_t^{IU}}{\lambda_t^{IU} + \lambda_t^{IE}} \lambda_t^{EI} + \lambda_t^{UE} + \frac{\lambda_t^{IE}}{\lambda_t^{IU} + \lambda_t^{IE}} \lambda_t^{UI}} \equiv \frac{s_t}{s_t + f_t} \tag{4}$$

Remember that λ_t^{AB} with $A \in \{E, U, I\}$ and $B \neq A$ are the instantaneous transition rates. The overall inflow into unemployment s_t is divided by the sum of two terms. The first one has a direct interpretation since it refers to the job separation to unemployment λ_t^{EU}. The second one $\frac{\lambda^{IU}}{\lambda^{IU}+\lambda^{IE}}\lambda^{EI}$ has a less obvious interpretation. This term multiplies the job separation to inactivity λ_t^{EI} by the part of outflows from inactivity towards unemployment. It captures the possibility of transiting from employment to inactivity (which influences the unemployment rate via the size of labor force) and from inactivity to unemployment (which influences the unemployment rate via the stock of unemployed). To sum up, this term can be seen as the indirect inflow rate from employment to unemployment via inactivity. The second term in denominator f_t has a similar interpretation.

Following Petrongolo and Pissarides (2008) and Smith (2011), we can decompose the steady state unemployment rate fluctuations into separable terms, attributable to the contributions of inflows and outflows. To do this decomposition we have to differentiate equation (4):

$$u_t^* - u_{t-1}^* = \frac{s_t}{s_t + f_t} - \frac{s_{t-1}}{s_{t-1} + f_{t-1}}$$

$$\Delta u_t^* = (1 - u_t^*) u_{t-1}^* \frac{\Delta s_t}{s_{t-1}} - u_t^* (1 - u_{t-1}^*) \frac{\Delta f_t}{f_{t-1}}$$

$$\Delta \frac{u_t^*}{u_{t-1}^*} = (1 - u_t^*) u_{t-1}^* \frac{\Delta s_t}{s_{t-1}} - \left(\frac{u_t^*}{u_{t-1}^*}\right) (1 - u_{t-1}^*) \frac{\Delta f_t}{f_{t-1}} \tag{5}$$

$$\Delta u_t^* = C_{s_t}^* + C_{f_t}^*$$

$C_{s_t}^*$ assesses the contribution of variations in the inflow rate to fluctuations in the steady state unemployment rate. $C_{f_t}^*$ assesses the contribution of variations in the outflow rate to fluctuations in the steady state unemployment rate. In equation (4) we have noticed that s_t and f_t are subdivided into two terms. Without loss of generality, we can separate each of these contributions into two sub-terms. The first one corresponds to the direct transition which implies jointly employment and unemployment. The second one is the indirect transition rate through inactivity. So:

$$\Delta s_t = \Delta\lambda_t^{EU} + \Delta\left(\frac{\lambda_t^{IU}\lambda_t^{EI}}{\lambda_t^{IU}+\lambda_t^{IE}}\right)$$

$$\Delta f_t = \Delta\lambda_t^{UE} + \Delta\left(\frac{\lambda_t^{IE}\lambda_t^{UI}}{\lambda_t^{IU}+\lambda_t^{IE}}\right)$$

We can now express the contribution of inflows to unemployment $C_{s_t}^*$ as:

$$C_t^{*EU} = (1-u_t^*)u_{t-1}^*\frac{\Delta\lambda_t^{EU}}{s_{t-1}} \ , \ C_t^{*EIU} = \frac{(1-u_t^*)u_{t-1}^*}{s_{t-1}}\Delta\left(\frac{\lambda_t^{IE}\lambda_t^{UI}}{\lambda_t^{IU}+\lambda_t^{IE}}\right) \tag{6}$$

Similarly, we can write the contribution of outflows from unemployment $C_{f_t}^*$ as:

$$C_t^{*UE} = -\left(\frac{u_t^*}{u_{t-1}^*}\right)(1-u_{t-1}^*)\frac{\Delta\lambda_t^{UE}}{f_{t-1}} \ , \ C_t^{*UIE} = -\left(\frac{u_t^*}{u_{t-1}^*}\right)\frac{(1-u_{t-1}^*)}{f_{t-1}}\Delta\left(\frac{\lambda_t^{IE}\lambda_t^{UI}}{\lambda_t^{IU}+\lambda_t^{IE}}\right) \tag{7}$$

As presented in equations (6) and (7), the contributions do not provide an intuitive interpretation of unemployment driving forces. Fujita and Ramey (2009) demonstrate that equation (5) can give a quantitative assessment of contribution by an exact decomposition of variance of u^*. They notice that equation (5) is a linear decomposition of u^* variations:

$$var(\Delta u_t^*) \approx cov(\Delta u_t^*, C_{st}^*) + cov(\Delta u_t^*, C_{ft}^*) \tag{8}$$

By dividing each covariance by the variance of Δu_t^*, we obtain a single statistic assessment of the contribution to unemployment fluctuations. This assessment denoted by β can be interpreted as the proportion of steady state unemployment rate variance generated by the contribution. For instance, the part of steady state unemployment rate attributable to the job separation rate is given by :

$$\beta^{EU} = \frac{cov(\Delta u_t^*, C_t^{*EU})}{var(\Delta u_t^*)} \tag{9}$$

	Contributions
Inflows	0,35
Outflows	0,65
β^{EU}	0,31
β^{EIU}	0,04
β^{UE}	0,46
β^{UIE}	0,19

Table 3: Unemployment decomposition under steady state approximationSource: FLFS (2003-2012).
Note: "Betas" are defined as the contribution of changes in transition rates to the variance of steady state unemployment.

Other "betas" are obtained in the same way. It follows that $\beta^{EU} + \beta^{EIU} + \beta^{UE} + \beta^{UIE} \approx 1$. All differences of the sum of betas to one are considered as residual approximation errors.

The results of the steady state decomposition with our data are reported in Table 3. Overall inflows to unemployment explain 35% of steady state unemployment variations. Overall outflows from unemployment account for 65% of steady state variability. Thus, in the last decade outflows from unemployment are the most determinant to understand unemployment variations.

When we decompose the overall inflows and outflows the results are slightly different. The job finding rate λ^{EU} is the first driver of unemployment dynamics since it generates 46% of steady state unemployment variations. The second driver of unemployment dynamics in France is the job separation rate. 31% of steady state variance is explained by job separation. In sum, approximately 77% of fluctuations in the unemployment steady state can be attributed to transitions between employment and unemployment. These results are in line with preliminary analysis of section 4. However, the role of flows between inactivity and labor force in explaining unemployment fluctuations is not marginal. Transition rates via inactivity explain 23% of unemployment fluctuations. Within these transitions, it is the indirect transition from unemployment to employment via inactivity which is dominant in explaining steady state fluctuations.

5.2 Is the steady state approach justified for the French economy?

The decomposition of the previous sub-section is based on the assumption that the current unemployment rate does not deviate from its steady state counterpart. This strong assumption can induce misleading results. If the steady state unemployment is the target of the actual unemployment, nothing ensures that the rate of convergence between them is low. Initially, the first decompositions of unemployment rate fluctuations consider the U.S. labor market. Authors as Shimer (2012), Fujita and Ramey (2009) or Elsby et al. (2009), among other, make the assumption that the steady state unemployment rate is a very good approximation to the unemployment rate. For the U.S. economy this hypothesis is not problematic, since the level of worker flows and transition rates associated is high. Indeed, the higher the level of transition rates is, the faster the convergence between unemployment rate and its steady state value is. However, along the lines of Elsby et al. (2013) we may anticipate that the steady state approximation may be inaccurate for labor market with low transition rates, as in Continental European economies. These authors notably pay attention to the French case by emphasizing that steady state decomposition do not work well for France[3].

The figure 6 compares our estimations of the French unemployment rate with its steady state value over the last decade. The current unemployment rate tends to co-move with the steady state. However, for some points, there is substantial discrepancy between the two series. The steady state unemployment is the target of actual unemployment and guides its variations. However, this target is not necessarily reached. According to our estimations, the half life time, which indicates the necessary duration for the current unemployment to offset the half of its delay with its equilibrium value, is about 5 months. Furthermore, the average logarithm deviation between the two unemployment rates is 3%, with a standard error of 5,1%. As mentioned above, the deviations between actual unemployment and steady state are essentially explained by the relatively low level of transition rates in the French labor market. Thus, contemporaneous variations in the transition rates have only a limited contemporaneous effect on unemployment fluctuations. For example, when an employed worker looses his job, he takes a long time to find another one. The contemporaneous variations in inflows/outflows rates influ-

[3] Elsby et al. (2013) note that, in annual french data, the standard error of logarithm deviation of unemployment from its steady state value amount to 5,1%. As a consequence, the residual of steady state approximation is very high (37%).

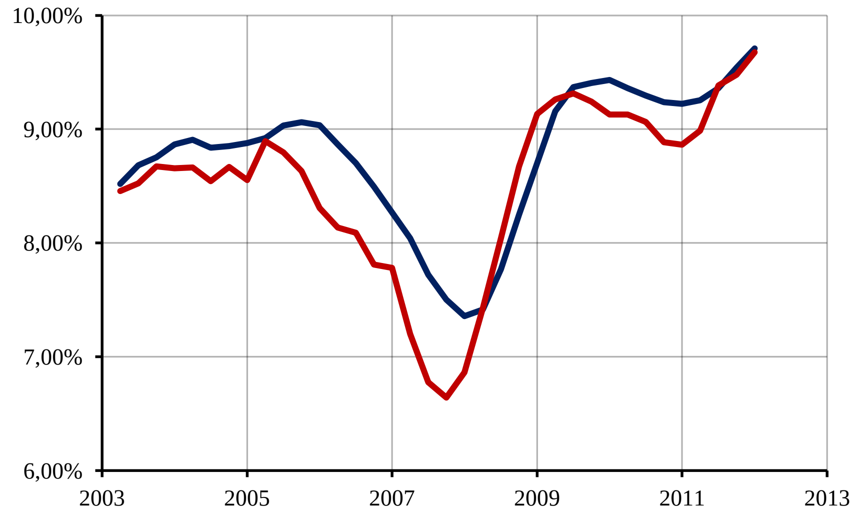

Figure 6: Comparison between current unemployment rate (in blue) and steady state (in red).
Source: FLFS (2003-2012), author calculations. The series are removed for seasonnality with x12 arima process. The two series are a three-quarters moving average

ence not only the contemporaneous unemployment variations but also its future changes. So, unemployment dynamics depend on current changes as well as past changes in transition rates. Finally, this indicates that the use of steady state unemployment as a proxy for its current level is a strong assumption that should be removed. That's why, in the next sub-section we present the results of a decomposition which allows for deviation of actual unemployment from its steady state value.

5.3 Beyond the steady state aprroach

Smith (2011) develops a dynamic framework which allows current unemployment to deviate from the steady state. This decomposition expresses the unemployment fluctuations as the result of both contemporaneous and past changes in rates of inflows to and outflows from unemployment. By using s_t and f_t as in the sub-section 3.1, we can express the law of motion of unemployment rate:

$$\dot{u}_t = s_t(1 - u_t) - f_t u_t$$

By rearranging this last equation, the unemployment rate can be defined as:

$$u_t = \frac{s_t}{s_t + f_t} - \frac{du_t}{d_t}\frac{1}{s_t + f_t} \tag{10}$$

Equation (10) shows how the the level of transition can influence contemporaneous unemployment rate. If transition rates are high, the second term of the right hand side of (10) tend to 0. In this case, the actual and the steady state unemployment are similar, and, the latter is a good approximation of the former. By differentiating and rearranging (10) we obtain a second order differential equation:

$$\frac{d^2u_t}{dt} = \frac{1}{s_t + f_t}\left(f_t\frac{ds_t}{dt} - s_t\frac{df_t}{dt}\right) + \frac{du_t}{dt}\left(\frac{1}{s_t + f_t}\frac{d}{dt}(s_t + f_t) - (s_t + f_t)\right)$$

The last equation can be treated as a first-order differential equation in $\frac{du_t}{dt}$. Returning to a discrete time specification and rearranging, we obtain a recursive expression for changes in current unemployment:

$$\Delta u_t = \frac{(s_t + f_t)(s_{t-1} + f_{t-1})}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}\Delta u_t^* + \frac{(s_t + f_t)}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}\Delta u_{t-1} + \epsilon$$

$$\frac{\Delta u_t}{u_{t-1}^*} = \frac{(s_t + f_t)s_{t-1}}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}\Delta u_t^* + \frac{(s_t + f_t)}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}\Delta u_{t-1} + \epsilon \tag{11}$$

According to equation (11) current unemployment variations are expressed as the sum of two terms. The first one corresponds to contemporaneous (percentage) variations in steady state unemployment weighted by the rate of convergence between u and u^*. The second one represents the past changes in actual unemployment. The importance of this term is much stronger if transitions rates on the labor market are low.

The relative contributions of inflows to and outflows from unemployment are deduced from (11). The contribution of outflows from unemployment is:

$$C_t^f = \frac{(s_t + f_t)(s_{t-1} + f_{t-1})}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}C_t^{*f} + \frac{(s_t + f_t)}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}C_{t-1}^f \text{ with } C_0^f = 0 \tag{12}$$

and the contribution of inflows:

$$C_t^s = \frac{(s_t + f_t)(s_{t-1} + f_{t-1})}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}C_t^{*s} + \frac{(s_t + f_t)}{s_{t-1} + f_{t-1} + (s_t + f_t)^2}C_{t-1}^s \text{ with } C_0^s = 0 \tag{13}$$

With C_t^{*f} et C_t^{*s} are the relative contributions of inflows/outflows under the steady state approximation, defined above in equation (6) and (7). As in the steady state approximation, we can divided the overall inflows/outflows contributions in two sub-terms corresponding to direct transitions between employment and unemployment, and indirect transitions working through inactivity.

C_t^f and C_t^s do not catch all the unemployment rate fluctuations. There is a relative contribution due to the initial condition for period $t = 0$.

$$C_t^0 = \frac{(s_t + f_t)}{s_{t-1} + f_{t-1} + (s_t + f_t)^2} C_{t-1}^0 \text{ with } C_0^0 = \Delta u_0 - \Delta u_0^* \tag{14}$$

Along the lines of Hertweck and Sigrist (2013) we compute the relative contributions of inflows/outflows to unemployment variations in two stages. In a first step, we compute the contribution of the unemployment rate fluctuations generated by the dynamic decomposition[4] in current unemployment rate fluctuations. This contribution is denoted by β^U.

$$\beta^U = \frac{cov(\Delta u_t, \Delta u_t^{dd})}{var(\Delta u_t)}, \;\; \beta^\epsilon = \frac{cov(\Delta u_t, \epsilon)}{var(\Delta u_t)} \tag{15}$$

In a second step, we quantify the "betas" between unemployment variations generated by the dynamic decomposition and inflows/outflows variations as expressed in (12) and (13):

$$\beta^i = \frac{cov(\Delta u^{dd}, C_t^i)}{var(\Delta u_t^{dd})} \text{ with } i \in \{s, f, EU, EIU, UE, UIE\} \tag{16}$$

In this framework, β^i mechanically sum to one.

The "beta-values" obtained with the dynamic decomposition are reported in table 4. First, note that the the overall model fits β^U accounts for 74% of unemployment fluctuations. In other words, the non-steady state decomposition fails to explain 26% of unemployment changes. According to Hertweck and Sigrist (2013), this discrepancy can be explained by the initial condition, sampling errors and the violation of implicit maintained hypothesis (constant transition rates within a quarter, no labor force groxth, linearity etc.). The bottom panel of figure 7 shows that the overall unemployment fluctuations fit by the dynamic decomposition tracks very well unemployment rate changes. So, we consider that changes

[4]The unemployment rate variations generated by the model correspond to the right-hand side of equation(11).

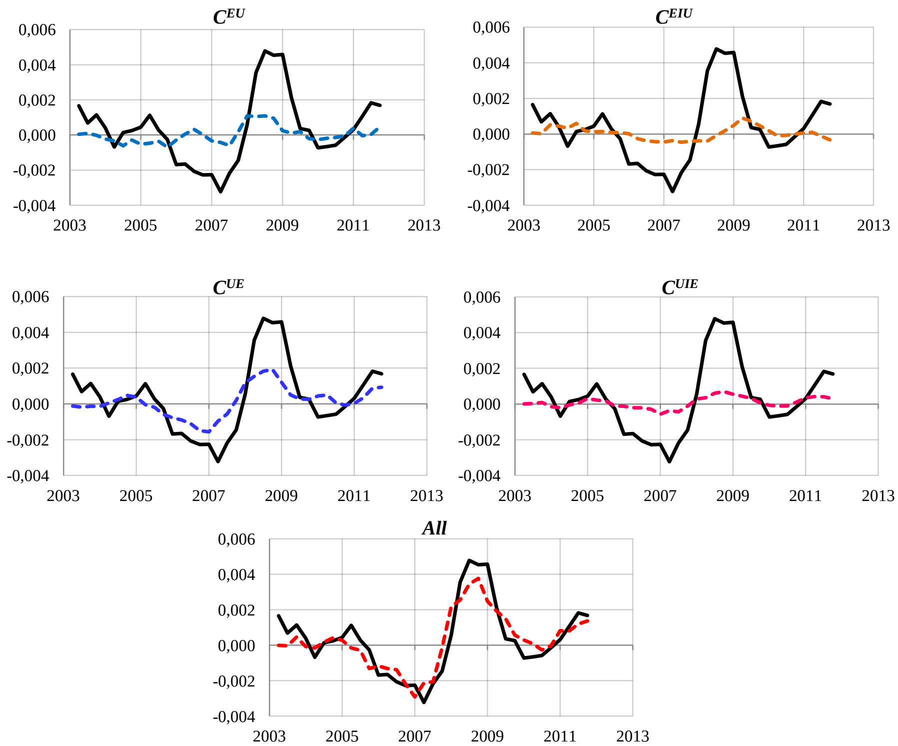

Figure 7: Contribution of transition rates in unemployment variation Δu_t (in black).

in unemployment are sufficiently explained by the non-steady state decomposition.

The "beta-values" obtained by the second step are close to those obtain by the steady state decomposition. The overall inflows/outflows contributions indicate that the outflows from unemployment dominate in explaining French unemployment rate fluctuations (approximately 70%). Although, the role of inflows is not marginal, the dynamic decomposition reveals the importance of the outflow process in shaping unemployment.

The detailed analysis of transition rates reiterates the conclusions of the decomposition under the steady state approximation. The job finding rate is the first determinant of French unemployment and explains the half of its fluctuations. Comparatively to the steady state decomposition, the role of job separation rate is reduced with the dynamic decomposition, since, now it accounts for 22% of unemployment rate variations. Finally, transitions between participation and non-participation are not negligible and generate 27% of unemployment variations. Within these relative contributions, transition between unemployment to employment via inactivity is dominant by accounting for 18%.

According to our estimations, the role of the job finding process is dominant in the dynamics of French unemployment during the last decade and notably during the Great Recession. This result is consistent with those of Hairault et al. (2015), even if the order of magnitude is slightly different. With a "two-state" view of the French labor market, they conclude that[5] the job finding rate explains 59% of unemployment variations[6]. However, our results are different from theirs for two reasons. First, we find that the role of the job separation rate is relatively low (22% against 40%). Second, our dynamic decomposition shows that transitions between labor force and not-in-labor-force are not negligible. Hairault et al. (2015) argue[7] that the unemployment variations are not significantly affected by transition rates involving inactivity. Their decomposition leads to the results that only 7% of unemployment variability can be explained by these flows. Our estimations indicate that transition rates involving inactivity account for one quarter of unemployment variance. The different databases and definitions of labor market states used across these two studies can justify this discrepancy. When individuals recall their labor market status, with relatively an unclear definition of inactivity, the cyclicality of transition involving inactivity is marginal. However, when inactivity is defined according to the ILO's standard, the cyclicality of inactivity is higher. The ILO's standard used in this paper captures better the flows between participation and non-participation, and consequently, their influences in shaping unemployment.

As unemployment fluctuations are mainly dictated by the outflows process, it is necessary to focus on the return to job to reduce unemployment. Economic policies may improve employability of unemployed workers. Note that these policies can take two forms. First, in the supply side the unemployed workers need to be helped when they are searching for a job. Second, in the demand side, incentive measures should be taken in order to reduce hiring and labor cost.

[5]Cf. Hairault et al. (2015), Table 7.

[6]This result is robust to the specification of the labor market. With a "three-state" approach, and under the steady state approcimation, (cf. (Hairault et al., 2015), Table 11, appendix E) the relative contribution of the job finding is estimated to 62%.

[7]Cf. appendix E Hairault et al. (2015)

	β^U	β^s	β^f	β^{EU}	β^{EIU}	β^{UE}	β^{UIE}
All	0,74	0,31	0,69	0,22	0,09	0,51	0,18
Women	0,74	0,21	0,79	0,06	0,15	0,64	0,15
Men	0,73	0,41	0,58	0,32	0,09	0,42	0,16
15-24 y.o	0,66	0,31	0,70	0,26	0,05	0,56	0,14
25-49 y.o	0,60	0,32	0,68	0,22	0,10	0,55	0,13
50-64 y.o	0,59	0,37	0,63	0,19	0,18	0,28	0,35
Education 1	0,50	0,42	0,58	0,34	0,08	0,36	0,22
Education 2	0,82	0,35	0,63	0,26	0,11	0,48	0,15
Education 3	0,41	0,33	0,67	0,04	0,29	0,51	0,16

Table 4: Non-steady state decomposition

6 Unemployment dynamics across sub-groups

Up to now we have taken into account the labor market at the aggregate level of the economy. This assumption can hide substantial differences between workers, since, in this approach workers are considered homogeneous. In this section, we relax this assumption by dividing the overall population into sub-groups according to gender, age and qualification. We replicate the dynamic decomposition developed in the previous section.

6.1 Gender

The first column of the table 5 reveals that the female unemployment rate is higher than the men unemployment rate. The French women are more likely to leave the labor force. Note that the job finding rate and the job separation rate are broadly similar for these two sub-groups. Finally, our estimations of worker flows for men and women reveal that their probabilities to leave inactivity are not significantly different.

Let us now turn to an analysis of their unemployment driving forces (table 4). The dynamic decompositions in each sub-group account for approximately three quarter of unemployment variations as for the overall population. Once again, we consider that the overall unemployment variations fitted by the decomposition are satisfying. The sharing between inflows to and outflows from unemployment is more balanced for men than women. By accounting for 79% of unemployment changes, the role of outflows in the driving force of female unemployment rate is sharply dominant. The job separation rate explains only 6% of female un-

	Unemployment rate	p^{EU}	p^{EI}	p^{UE}	p^{UI}	p^{IE}	p^{IU}
All	8,80	1,79	2,06	22,35	16,48	3,68	3,86
Women	9,42	1,81	2,43	22,34	18,52	3,52	3,83
Men	8,24	1,77	1,73	22,40	14,37	3,93	3,90
15-24 y.o	21,00	5,82	7,15	27,64	18,59	4,84	3,42
25-49 y.o	7,89	1,59	1,14	22,64	14,55	6,90	9,98
50-64 y.o	6,07	0,85	2,75	13,33	20,40	1,10	1,42
Education 1	14,38	2,41	2,59	15,97	17,97	1,93	3,56
Education 2	8,67	1,90	2,20	23,86	16,57	3,96	3,70
Education 3	5,67	1,25	1,52	28,33	13,90	7,11	5,40

Table 5: Average unemployment rate and transition rates across sub-groups (2003-2012)

employment dynamics. For men, the relative contribution of the job separation accounts for 32%. For both men and women the first determinant of unemployment variations is the job finding rate. Nonetheless, for men it explains 42% of unemployment variability whereas for women it explains 65%. Surprisingly, the relative importance of inflows/outflows from inactivity is only slightly more important for women than for men. The proportion of female unemployment variance generated by these transitions is equal to 30%. For men the transitions between participation and non-particpation account for 25%.

The women unemployment rate is more sensitive to the job finding process than their men counterpart. This finding suggests that during the Great Recession the chances of women to return to job have been sharply reduced. To reduce women unemployment it is necessary to understand this mechanism and to improve their abilities to access to job. For men, the message of the dynamic decomposition is slightly different and the role of the job separation process is more important. Based on these two sub-groups the dynamic decompositions reveal that the origins of unemployment are not the same, and consequently the solutions to reduce them also.

6.2 Age

Table 5 reveals substantial heterogeneity when the French population is divided according to the age. The young workers are the most atypical. Their unemployment rate is the highest and their transition rates are uncommon. The young job separation rate to unemployment or inactivity is three times higher than the average. The young workers are much more likely to move on the labor market than their counterparts. In contrast, the senior workers are broadly less likely to move. On average, their probabilities to return to job is weak. When they leave employment or unemployment, they move more frequently to the inactivity state. However, once inactive their chances to return to the labor force are very small. Finally, the outflows from inactivity are highest for middle-age worker. For the remainder, their transition rates are similar to the average.

The non-steady state decomposition provides less satisfying results, in the extend of, no more than 66% of unemployment variations are explained by the model for any subgroups. The older workers are the most atypical. Most prominently, the indirect transitions via inactivity have a dominant role and explain 53% of the unemployment fluctuations of senior workers. In contrast, the young and middle-age unemployment rates are essentially affected by direct transitions between employment and unemployment, the job finding process being each time the most important. However, the young workers are more sensitive to the cyclicality of the job separation rate. This indicates that during economic downturns, young workers are more likely to leave employment. Only 19% of changes in young unemployment rate are explained by inflows to and outflows from inactivity. Finally, the middle-age workers exhibit unemployment dynamics very close to the average.

These decompositions show that the determinats of unemployment of senior workers are really specific. The role of the entries in and exits from the labor force is prevailing. The proximity to retirement may explain this mechanism. Furthermore, it seems that the old workers face several difficulties to rejoin the labor force and employment. For them, it is important to prevent their exits from the labor force. On the overall, for the young and middle-age workers the role of flows in shaping their unemployment rate is close to the average. To prevent the rise in unemployment of these two populations, it is crucial to focus on their chances to find a new job. For the young employed workers the job separation should be considered with more attention. The fact that this population is more flexible[8] may explain this stylized fact.

[8] The short term contracts are more important for young worker.

6.3 Qualification

Let us first explicit the three levels of education used in Table 4 and 5. Education 1 corresponds to individuals who completed their studies without graduating (unskilled). Education 2 refers to individuals who obtain, for the best, a degree of "baccalaureat" level[9] (low-skilled). Finally, Education 3 represents people who have graduated at a superior level than the "baccalaureat" (skilled).

The last three lines of Table 5 give the main stylized facts about the labor market for these sub-groups. It appears that the unemployment rate decreases with the level of education. For transition rates the picture is the same, and, the best path is followed by the skilled workers. Thus, the probability to separate from a job to unemployment or inactivity decreases with the qualification. In contrast, the higher is the level of qualification, the higher is the probability to find a job. Note that, the outflows from inactivity are more frequent for skilled workers. The sub-division of the overall population according to qualification reveals that the unskilled workers experience the most complicated path on the labor market. They leave unemployment for employment less frequently, once employed their chances to return to unemployment or inactivity are the highest. Finally, once the unskilled workers are inactive they are less likely to return to labor force.

The proportion of unemployment variations unexplained by the dynamic decomposition is very important for the unskilled and the skilled workers. Respectively, 50% and 59% of unemployment changes remain unexplained. However, for the low-skilled workers, only 18% of their unemployment rate fluctuations is unexplained by the non-steady state decomposition (see table 4). The sharing between outflows from and inflows to unemployment is more balanced for the unskilled workers. Thus, the job separation rate accounts for 34% of unemployment variance and the job finding rate accounts for 36%. The entries and exits of inactivity explain 30% of unskilled unemployment changes. The driving forces of unemployment are close to the average for the low-skilled workers. Surprisingly, the role of inactivity in shaping skilled unemployment variation is important, since it accounts for 45%. The contribution of the job separation rate to unemployment fluctuation of skilled workers is relatively unimportant (4%). As expected, the skilled workers is relatively protected when they have a job.

[9] The French equivalent to the A-level.

7 Conclusion

Our paper is the first to use the FLFS to analyze worker flows according to ILO's standards. We shows that flows jointly involving employment and unemployment are the most sensitive to economic conditions. Job separations (gross flow and transition rate) have sharply increased during the great recession and are counter-cyclical. Job finding gross flow exhibits unclear cyclical pattern and seems to be contemporaneously pro-cyclical. However, for some leads the last one is counter-cyclical. In contrast, the job finding probability is clearly pro-cyclical and its level is relatively low since 2008. The cyclical characteristics of flows between labor force and inactivity are lower.

We also evaluate the relative contributions of each transition rate on unemployment fluctuations. We find that inflows and outflows from unemployment do not contribute equally to French unemployment dynamics. The outflows process is clearly dominant in shaping French unemployment. The detailed analysis reveals that the job finding rate is the main driver of unemployment fluctuations (51%) and the job finding rate is the second (23%). This decomposition also demonstrates that the role of transitions between labor force and inactivity is not negligible and accounts for one quarter of unemployment fluctuations. We also show that it is important to take into account the heterogeneity of the population. By dividing the overall French population into sub-groups according to gender, age and qualification, we illustrate that for some sub-groups the origins of unemployment variations are different. Thus, women are more affected by the job finding process than men. Flows between participation and non-participation explain a large proportion of old unemployment variations. Finally, the dynamic decomposition demonstrates that the unemployment rate of unskilled workers are more sensitive to the job separation rate, whereas for the skilled workers, the inflows/outflows from inactivity play an important part. In most cases, the dynamic decompositions on these sub-groups reiterate the main conclusion of this paper: the job finding rate is the most determinant factor in explaining French unemployment variations.

This study contributes to the debate on the determinants of French unemployment dynamics by focusing on unconditional analysis. However, depending on the availability of the data, we share the idea that future researches should investigate the role of well-identified structural shocks on the French labor market dynamics. Since the French economy is relatively specific, the propagation mechanisms could be different from those well-documented for the U.S. economy, and depending on the source of structural shocks. This structural approach is probably also enlightening. However, these problematics are beyond the scope of this paper, but they are on our agenda for future researches.

Appendices

A Computing the longitudinal weights

The FLFS is the most reliable database to capture individual transitions on the French labor market. As mentioned in the main text, each household is interviewed six times, once per quarter. By matching individuals interviewed between two waves, it is easy to compute worker flows between two distinct periods. Nonetheless, this precious information is not directly useful. First, the sample of FLFS is a rotating panel. Each quarter, approximately one sixth of the sample is renewed. Consequently, in the best case only five sixth of a sample in period t is available to compute worker flows. Secondly, between two waves, some individuals who have answered in period t do not respond in period $t+1$. The non-response phenomena is really problematic since it introduce a bias. For example, we may imagine that the non-respondents have a specific behavior in terms of mobility on the labor market. Consequently, the weights provide by the French National Institute of Statistics and Economic Studies is probably biased for an analysis based on the longitudinal sample. That is why, it is imperative to (re-)compute the individual weights in order to reduce these bias.

The non-response correction and the calibration in the FLFS since 2003

Classically, in random survey after the sample selection and the interview step, there are two steps of adjustment:

⇒ The non-response correction which aims to reduce the bias introduced by the non-response phenomena.

⇒ The calibration which aims to reduce sample fluctuations for some important variables of the survey.

Each of these adjustments use specific tools. The non-response bias is corrected by re-weighting techniques assuming a uniform response mechanism. The calibration has another goal: re-weight the sample to equalize the structure of the weighted sample with the known structure of the population for some important variables (for example the age pyramid). In fact, the weight changes must be as weak as possible in order not to deviate too much from the initial weights, which are assume unbiased.

Note that these two adjustments consist in re-weight the sample. Thus, we may imagine that an unique step of calibration replaces the separate treatments for non-response correction and sample fluctuation adjustments. Lundström and Särndal (1999) demonstrate that an unique step of calibration can reduce the non-response bias if calibration variables can explain the non-response phenomena. This technique is applied for the non-response correction and the sample fluctuation adjustments for the FLFS. This is also the process that we favor for re-weighting the longitudinal samples.

Theoretical framework of calibration

Let the population $P = \{1, \ldots, i, \ldots, N\}$ in which we select by simple random sampling a sample s of size n. We aim to have an estimation of the total of a certain variable of interest $T(Y)$:

$$T(Y) = \sum_{i \in P} y_i \tag{17}$$

In this simple case, the classical Horvitz-Thompson estimators of the total is:

$$\hat{T}(Y) = \sum_{i \in s} \frac{y_i}{p_i} = \sum_{i \in s} \frac{N}{n} y_i = \sum_{i \in s} d.y_i$$

With d the initial weights. This theoretical estimator although unbiased is not efficient if we dispose of a set of auxiliary variables correlated with Y. The exogenous variables J are known on the overall population and their total are also known:

$$T(X_j) = \sum_{i \in P} x_{ij}$$

The main objective is to deform the initial weights to have new weights which perfectly estimate the totals of the auxiliary variables X_j. However, the changes on the initial weights must be low to have unbiased new weights. So, the first constraint is to perfectly estimate $T(X_j)$. The second constraint consist in being closely to the initial weights which are unbiased. So we have:

$$\sum_{i \in s} d.x_{ij} \neq T(X_j)$$

There is no reason to have an equality between the totals of the sample weighted by the initial weights and the overall population for the auxiliary variables. We aim to have a new weight w_i which satisfy the following calibration equations

$$\sum_{i \in s} w_i x_{ij} = T(X_j), \forall j = 1, ..., J$$

The weights w_i is the final weights also called calibration weights. These calibrated weights must be closely to the initial weights to ensure that they are not biased. Thus, the main objective is to find the new weights which ensure the equalization of the totals for the calibration variables and minimize the sum of the distances between the initial and the calibrated weights. This last condition implies the choice (arbitrary) of a distance function denoted G which have for argument the distance between d_i and w_i $x = \frac{w_i}{d_i}$. The solving of this problem consists in a minimization program under constraints written as:

$$Min \sum_{i \in s} d_i G\left(\frac{w_i}{d_i}\right)$$

$$s.c \sum_{i \in s} = w_i x_i = X$$

With $x_i = (x_{1i}, \ldots, x_{ji})'$ and $X = (T(X_1), \ldots, T(X_J))'$ This optimation problem can be solve by writing the following Lagrangian:

$$\varphi = \sum_{i \in s} d_i G\left(\frac{w_i}{w_i}\right) - \lambda' \left(\sum_{i \in s} w_i x_i - X\right)$$

Now, identify this theoretical framework to our re-weight problem. The overall population in which we "select" the longitudinal sample is the FLFS sample in period t. The initial weights correspond to the weights provide by the institute. The totals of the auxiliary variables X_j is directly deduced from the FLFS sample weighted by the initial weights[10]. Finally, the final weights w_i is the calibrated longitunal weights. This step of calibration is repeated 39 times for each longitudinal sample.

Calibration variables

The choice of the calibration variables is crucial. In our procedure they must be sufficient to correct the bias introduce by the non-response and to reduce the sample fluctuations. The calibration variables used in our calibration are reported in table 6

[10]Implicitly, we assume that these estimations correspond to that of the French population

Variables	Levels
Age Pyramid/gender	five-year classes from 15 to 75 y.o.
Household type	5 classes: household of one person, single-parent families, couple without and with children
Labor market states in t	3 states: employment, unemployment, inactivity
Degree	5 levels: no graduate, - than "Bac", "Bac", "Bac + 2", ">Bac + 2"

Table 6: The calibration variables

Jeauneau and Nouël (2011) choose a variable which indicates the marital status, we opt for a more informative variable the household type. In our point of view, this choice is important notably for the non-response correction. In our calibration, we introduce the gender from the age pyramid. This is equivalent to introduce two age pyramids, one for men and one women. For us, it is crucial to have the labor market state as a calibration variables. We may imagine that the individual transitions are relied to the labor market states in peiod t. The better the estimations of stocks is, the better the estimation of worker flows is. Finally, we also add a variable who indicates the degree level. We assume that all these variables are sufficient to correct for the non-response bias and to provide good estimations of worker flows in France. All the stocks come from the FLFS in period t weighted by the initial weight provided by the French National Institute of Statistics and Economic Studies. We introduce 35 constraints in each calibration procedure.

An example

The example deals with the survey of the second and third quarter of 2011. We compare the officials stocks for the labor market states with the totals obtained from the longitudinal sample by applying two re-weights. The first one is that we have developed in the previous paragraphs. The second one is the "Missing At Random" (MAR henceforth) approach deliberately left out up to now. The MAR correction drops the missing observations between two quarters and re-weight the elements of the longitudinal sample by the inverse of the response probability. However, this method have two restrictive assumptions. On the one hand, the “non-response” in survey $t+1$ of individuals interviewed in t is considered as random. On the other hand, it supposes that the average behavior of the “non-respondents” is the same of the “respondents”. Clearly, this procedure may lead to bias the estimations in particular if types of transitions are different among “respondents” and “non-respondents”. The MAR procedure was used by Shimer (2012), justifying our comparison in this paragraph.

	Official Stocks		MAR weight				Calibrated weight			
	Stocks (A)	%	Stocks (B)	%	$A-B$	$\frac{A-B}{A}$	Stocks (C)	%	$A-C$	$\frac{A-C}{A}$
Employment	25 868 747	51,05	25 378 088	50,40	490 659	1,90	25 901 507	51,05	-32760	-0,13
Unemployment	2 465 530	4,87	2 296 777	4,56	168753	6,84	2 469 688	4,87	-4158	-0,17
Inactivity	22 340 773	44,09	22 674 929	45,03	-334 156	1,50	22 362 011	44,08	-21238	-0,10

Table 7: Comparison of the official stocks with longitudinal sample totals from the MAR and our own calibrated weights

The table 7 compare the official stocks of employed, unemployed and inactive workers with the totals obtained by the two re-weights. Not surprisingly, the totals obtained by the MAR weights differ the most from the official numbers provided by the institute. Thus with this re-weight, the employment stock is under-estimates of 1/2 millions people. In term of relative errors, we can see that the unemployed stock is under-estimates of about 7%. This finding may not be treated as negligible. We can note that the MAR weight tends to underestimate the size of the labor force and overestimate the size of inactivity. The calibrated weight provide results more satisfying. The discrepancies between the official stocks are sharply less important. The employment stock is under-estimated of about 0,13%, the unemployment stock of about 0,17% and the inactivity stock of about 0,09%. This demonstrates that the calibrated longitudinal sample provides better estimations of the stocks of the labor market states.

The table 8 displays the estimation of gross worker flows according to the two treatments. The MAR method tends to under-estimate the level of the worker flows on the French labor market. This finding indicates that the longitudinal sample contains on average less individuals who are likely to move on the labor market .

Gross worker flows	Calibrated weight (A)	MAR weight (B)	$A-B$
EU	483 892	462 062	-21 830
EI	612 456	601 584	-10 872
UE	546 959	502 097	-44 862
UI	430 376	403 805	-26 571
IE	613 789	567 039	-46 749
IU	475 146	457 180	-17 966

Table 8: Comparison of gross worker flows obtained according to the MAR and calibrated weights.

B Robustness of the cross correlation to the use of various filters

	HP $\lambda = 100000$					First order difference				
	-2	-1	0	1	2	-2	-1	0	1	2
p^{EU}	-0,46	-0,55	-0,55	-0,54	-0,50	-0,25	-0,11	-0,09	-0,07	-0,15
p^{EI}	0,41	0,41	0,33	0,27	0,06	-0,08	0,19	-0,03	0,28	-0,15
p^{UE}	0,25	0,46	0,57	0,60	0,57	0,04	0,33	0,30	0,30	0,19
p^{IE}	0,18	0,28	0,34	0,28	0,33	-0,02	0,12	0,11	-0,16	0,22
p^{UI}	0,01	0,14	0,16	0,17	0,16	-0,10	0,21	0,00	0,25	0,08
p^{IU}	0,11	-0,08	-0,23	-0,39	-0,50	-0,06	-0,00	0,05	-0,25	0,08
EU	-0,53	-0,60	-0,58	-0,53	-0,46	-0,26	-0,12	-0,11	-0,06	-0,14
EI	0,34	0,37	0,31	0,29	0,12	-0,09	0,17	-0,05	0,28	-0,14
UE	0,59	0,49	0,31	0,08	-0,13	0,15	0,29	0,06	0,04	-0,12
IE	0,14	0,23	0,28	0,27	0,35	-0,04	0,10	0,10	-0,17	0,22
UI	0,26	0,08	-0,14	-0,33	-0,47	0,02	0,18	-0,13	0,04	-0,14
IU	0,07	-0,12	-0,28	-0,41	-0,49	-0,08	-0,03	0,05	-0,28	0,00

Table 9: Robustness of the cyclical properties of the series to the filer used

The table 9 reveals that the cyclical properties of the series are not sensitive to the use of a higher smoothing parameter in the HP filter. However, when a first-order difference filter is used, the correlations are modified. This phenomenon is perceptible in most studies evaluating the cyclical properties of flows and may be explained by the weak properties of this filter method.

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