WORKER FLOWS, OCCUPATIONS AND THE DYNAMICS OF UNEMPLOYMENT AND LABOR FORCE PARTICIPATION

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Worker Flows, Occupations and the Dynamics of Unemployment and Labor Force Participation

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Abstract

Using Current Population Survey (CPS) data over the period 1976-2010 and the occupation classification of Autor and Dorn (2013) to rank occupations between high, medium and low skill, this paper provides a flow rate analysis of quarterly fluctuations in occupation-specific and aggregate stocks. I apply the variance decomposition developed by Elsby et al. (2015) and find that inflows (the ins) explain a higher share of the variance in the fluctuations of the high skill unemployment rate (around 54%), while outflows (the outs) account for 60% of the variance of the low skill unemployment rate variance. I then show how the variance decomposition for occupation-specific stocks can be used to study fluctuations of aggregate stocks, namely the unemployment and labor force participation rates. This allows to analyze the role of occupation-specific flow rates but also effects of variations in the occupational shares of employment and unemployment. The variance decomposition results indicate that compositional effects do not account for much of the variance in aggregate unemployment rate fluctuations. It is occupation-specific transition rates out and into unemployment that account for most of the variance in these fluctuations. Outflows and inflows explain 60% and 35% of the variance in unemployment fluctuations with flows into and out of middle and low skill unemployment contributing for 80%. I focus on labor force participation fluctuations in the last part of the paper. In addition to the occupation compositional effect, I find that outflows from the labor force are also affected by fluctuations of the unemployment rate: when unemployment increases, the transition rate out of the labor force increases as well given that unemployed have a much higher exit rate compared to employed workers. This compositional effect is also described by Barnichon (2019) and I find that it accounts for 34% of the variance in quarterly fluctuations of labor force participation. The remaining share is explained by inflows to the labor force (65%) with inflows to employment and unemployment contributing for 45% and 20% respectively.

Keywords: Worker flows; unemployment; occupations; labor force participation.
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1 Introduction

Understanding the dynamics of the labor market is a topic that attracted numerous contributions over the last 50 years. It is well known that the U.S. labor market is characterized by substantial worker flows between employment, unemployment and inactivity, which shape fluctuations of these 3 stocks. Early contributions on unemployment rate fluctuations (Darby et al. (1986), Blanchard and Diamond (1990)) focused on gross worker flows and emphasized the role of inflows to unemployment. More recent contributions have looked at the role of transition rates and reached opposite conclusion by highlighting the prominent role of outflows (Hall (2005), Shimer (2012)). Alternatively, Fujita and Ramey (2009) and Elsby et al. (2009) conclude that both inflows and outflows matter whereas Elsby et al. (2015) underline the role of transitions between unemployment and inactivity.

On the other hand, less contributions are focusing on the analysis of labor force participation fluctuations partly because this stock is less volatile and less correlated with GDP than unemployment. Moreover, standard model of the labor market have trouble in reproducing the mild procyclicality of this stock (Tripier (2004), Veracierto (2008), Shimer (2011)). The procyclicality of labor force is usually thought to capture a discouraged worker effect leading to an increase of outflows during recessions, as jobs are harder to find and individuals drop out of the labor force. Workers then re-enter as the economy recovers. These outflows are offset by other factors, in particular an increase of the transition rate from inactivity to unemployment during recession which can help explain the mild procyclicality of labor force participation (Mankart and Oikonomou (2016a)). Some recent contributions focusing on transition rates have challenged the discouraged worker mechanism. Elsby et al. (2015) show that the transition rate from unemployment to inactivity actually decrease during recessions as the unemployment pool shift towards more attached workers. Moreover, Barnichon (2019) and Elsby et al. (2019) apply a flow rates decomposition of labor force fluctuations and argue that the cyclical behavior of outlflows can be primarily explained by fluctuations of the unemployment rate. When unemployment increases, outflows from the labor force increase as the transition rate from unemployment to inactivity is much greater than the transition rate from employment.

This paper proposes to study the dynamics of labor market stocks by focusing on worker flows and transition rates disaggregated by occupations. More precisely, I use the Current Population Survey (CPS) for the period 1976-2010 and the occupation classification of Autor and Dorn (2013) to rank occupations between high, medium and low skill. I adjust series of stocks and flow rates for various issues (see Ounnas (2019)) and use these series to apply the variance decomposition proposed by Elsby et al. (2015). This decomposition measures the contributions of each flow rates to the fluctuations of labor market stocks. Thereby, I can provide an analysis of the fluctuations of disaggregated stocks (high, middle and low skill unemployment rates) but also study the effects of occupation-specific transition rates on the dynamics of aggregate unemployment and labor force participation.

Cortes et al. (2016) have recently taken a similar approach by looking at flow rates that can account for the decrease of middle skill employment originating from *Job Polarization* (Autor and Dorn (2013)). Their study focuses on medium run dynamics of middle skill employment without studying occupational unemployment rates or aggregate stocks. In this paper, only short run fluctuations of the unemployment and labor force participation rates are analyzed. Moreover, I use the variance decomposition of Elsby et al. (2015) to study the relation between transition rates and the dynamics of stocks.

The variance decomposition results for occupation-specific unemployment rates show that fluctuations of the high skill unemployment rate are mostly driven by inflows (54% of the variance) while outflows explain the largest share of the variance (60%) in the low skill unemployment rate variance.

To study aggregate stocks fluctuations, I show how to derive aggregate transition rates expressed in terms of transition rates by occupations. I decompose variations of aggregate transition rates into a (disaggregated) hazard rate effect, and a composition effect originating from changes in the occupational composition of employment and unemployment. It turns out that composition effects only explain a very small share of the variance of the aggregate unemployment rate. I find that outflows from unemployment account for around 60% of the variance of aggregate unemployment fluctuations while inflows explain around 35%. This confirms that both ins and outs matter to understand fluctuations of the unemployment rate (Elsby et al. (2009), Fujita and Ramey (2009)). Moreover, I find that middle and low skill unemployment outflows and inflows account for 80% of the variance of the aggregate unemployment rate.

For labor force participation, I show that the aggregate outflow rate can also be decomposed into a disaggregated hazard rate effect and a composition effect. The composition effect captures variations of the occupational composition of (un)-employment but also effects from unemployment rate fluctuations as described by Barnichon (2019) and Elsby et al. (2019).
The variance decomposition results imply that outflows from the labor force explain around 34% of the variance of labor force participation and unemployment rate variations account for the entirety of this contribution. This result confirms the central role of unemployment variations in driving outflows from the labor force. The graphical analysis of contributions also reveals that transition rates from unemployment to inactivity act as an offsetting force. During recessions, these transition rates decrease (see Elsby et al. (2015)) which lowers outflows from the labor force. This negative effect on outflows compensate the positive effect coming from the increase of the unemployment rate and contributes to dampen labor force fluctuations. The variance decomposition also highlights the role of inflows to the labor force which explain the remaining share of the variance (around 65%). This substantial contribution comes primarily from inflows to employment (45%) in particular to middle and low skill occupations. Similarly to outflows, the graphical analysis of inflows shows that hazard rates to employment and unemployment act as opposing forces. In recessions, the inflow to employment decreases which has a negative effect on labor force participation. On the other hand, the inflow to unemployment increases which compensate the negative effect from the inflow to employment. The fluctuations of labor force participation are therefore the results of different hazard rates and composition effects which compensate each other and contribute to the mild procyclicality of this stock.

The paper is organized as follows. In Section 2, I present the data and briefly review some cyclical properties of labor market stocks and flow rates. The framework for the variance decomposition of Elsby et al. (2015) is explained in Section 3. Lastly, the results of the decomposition are discussed in Section 4. Section 5 concludes the paper.

2 Data

2.1 Data Description

Elsby et al. (2015) propose a variance decomposition of labor market stocks fluctuations that they apply to the aggregate unemployment rate in the US from 1968 to 2012. This decomposition relies on discrete and continuous time transition rates. To compute those rates, I use the monthly Current Population Survey (CPS) for the period 1976-2010 and restrict the sample to individuals aged 16 and over.[1] Each month, the CPS assigns detailed occupation (3-digit) codes to employed (unemployed) workers according to their current (last) job. No occupation codes are assigned to workers who enter the labor market for the first time (*New unemployed entrants* in the CPS). These individuals are therefore dropped from the sample. I use the occupation-task classification developed by Autor and Dorn (2013) to rank each detailed occupation between high, medium and low skill. Note that Autor and Dorn (2013) classify occupations according to their task content. Hence, high skill occupations should be understood as cognitive intensive tasks occupations, middle skill as routine intensive tasks occupations and low skill as manual task intensive occupations. Table 1 displays the classification.

[1] I restrict the analysis to December 2010 given that a new occupational classification is introduced by the BLS in January 2011.

Occupations	Abstract/Cognitive tasks	Routine tasks	Manual tasks	skill level
Managers/prof/tech/finance/public safety	+	-	-	*high*
Production/craft	+	+	-	*middle*
Transport/construct/mech/mining/farm	-	+	+	*low*
Machine operators/assemblers	-	+	+	*middle*
Clerical/retail sales	-	+	-	*middle*
Service occupations	-	-	+	*low*

The first 4 columns of this Table are taken from Table 2 of Autor and Dorn (2013). A "+" indicates that the task value of a given occupation-group is above the task value averaged over all occupation-groups. The shaded cells give the maximum task value for each occupation-group. I assign a skill level to an individual occupation according to whether the task value of the occupation-group she belongs to is more abstract (high skill), routine (middle skill) or manual (low skill).

Table 1: Occupation classification

The computation of labor market stocks, flows and hazard rates is performed in 2 steps. First, population stocks can be obtained from monthly CPS files. The 3 group occupation classification implies that there are 7 labor market states; high, middle and low skill employment (E^h,E^m and E^l) and unemployment (U^h,U^m and U^l), with I standing for inactivity. The computation of gross flows requires to match CPS files for 2 consecutive months and I follow Madrian and Lefgren (1999) to perform the matching. Stocks and gross flows time series further have to be adjusted for various problems. These include breaks originating from the 1994 redesign of the CPS questionnaire, updates in occupational classifications (every 10 years or so) and new population estimates. These issues and the method used to correct them are presented in detail in Ounnas (2019). The seasonal adjustment of series is also carried out during this step. Thus, the first step allows to obtain adjusted time series of stocks, and flow rates are computed from the adjusted gross flows.

In a second step, I use these series to compute continuous time transition rates and retrieve transition rates adjusted for the time aggregation bias. The correction for this bias relies on the close links between discrete and continuous time Markov chains. Whereas the correction applied by Shimer (2012) and Elsby et al. (2015) is easily implemented and requires to perform an eigenvalue decomposition of the discrete time transition matrix, I cannot apply this method to the data used in this work.[2] As a results, I use the Bayesian estimation technique proposed by Bladt and Sørensen (2005). Although the method used to compute hazard rates is different, Ounnas (2019) shows that the adjusted transition rates are similar to those reported by Shimer (2012) and Elsby et al. (2015).

However, It should be noted that I do not correct for misclassifications errors between unemployment and inactivity (Abowd and Zellner (1985) and Poterba and Summers (1986)),[3] as it would require assuming that the misclassification probabilities estimated for aggregate stocks E, U and I, are equal across high, middle and low skill occupations. Another potential source of problems is related to spurious occupational mobility (Kambourov and Manovskii (2013)) which inflate transitions rates between occupation groups (e.g. from U^h to E^m or from E^h to E^m). See Ounnas (2019) for more details on these issues.

[2]See Ounnas (2019) and the discussion in Section 3.1 on restrictions specific to occupational data and transitions to unemployment.

[3]Note that Kudlyak and Lange (2017) cast doubt on the fact that frequent transitions between unemployment and inactivity capture misclassification errors. By matching individuals in the CPS for 4 consecutive month, they show that individuals frequently transitioning between unemployment and inactivity have a job finding probability 5 times larger than individuals inactive for consecutive months. Furthermore, frequent movers have lower wages when finding jobs than those unemployed. Kudlyak and Lange (2017) claim that these 2 facts rule out misclassification errors for these frequent movers who appear to be different from individuals consistently reporting to be unemployed or inactive.

2.2 Cyclical Properties of Stocks and Flows

Cyclical properties for aggregate series (without the occupation dimension) are well known (Darby et al. (1986), Blanchard and Diamond (1990), Fujita and Ramey (2009), Krusell et al. (2017)). However, properties for high, middle and low skill series are largely unknown, in particular for flow rates.[4] The cyclical component is computed as 100 times the log deviation from the trend extracted using the HP-filter with smoothing parameter $\lambda = 1600$.[5]

Table 2 presents results for quarterly averages of aggregate and occupation-specific stocks. These stocks are normalized by total population[6] implying that $E_t^h + E_t^m + E_t^l + U_t^h + U_t^m + U_t^l + I_t = 1$. Therefore, employment series are employment to population ratios (with $E_t = E_t^h + E_t^m + E_t^l$) and the aggregate labor force participation rate is $\text{lf}_t = 1 - I_t$. Table 2 also displays results for unemployment rates (e.g. $u_t^h = \frac{U_t^h}{E_t^h + U_t^h}$). The cyclical properties for aggregate series are in line with what is usually reported. Employment is strongly correlated and slightly less volatile than GDP. On the other hand, the unemployment rate is highly volatile (around 7 times that of GDP) and negatively correlated with GDP. The labor force participation rate is the least volatile series and is mildly procyclical. The correlation with GDP is slightly higher than what is usually reported although this higher figure could originate from the deseasonalization procedure. Furthermore, Van Zandweghe (2017) argues that the correlation between the participation rate and GDP increased over time exhibiting a break that he traces to 1984. Prior to 1984, Van Zandweghe (2017) reports a correlation of .2 while post 1984, the correlation rises to 0.5 in line with the results of Table 2.

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Employment to population ratio				
E	0.0101	0.693	0.866	0.901
E^h	0.0095	0.652	0.542	0.697
E^m	0.0147	1.017	0.779	0.800
E^l	0.0135	0.931	0.740	0.685
Unemployment rate				
u	0.1123	7.749	-0.883	0.918
u^h	0.1332	9.189	-0.811	0.888
u^m	0.1160	8.000	-0.875	0.890
u^l	0.1047	7.220	-0.885	0.899
Labor force participation rate				
lf	0.0036	0.248	0.520	0.656

The cyclical component x_t is extracted as 100 times the log deviation from the HP-filter trend with smoothing parameter $\lambda = 1600$. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 2: Cyclical Properties for quarterly average of stocks over the period 1976-2010

[4] Foote and Ryan (2015) use a different classification and focus mostly on stocks and flows from and to their measure of middle skill unemployment.

[5] Following the critics made by Hamilton (2018) on the limits of the HP-filter, I also extract the cyclical component using his proposed filter. The results are not qualitatively affected by this alternative set-up for trend extraction. These results are presented in Appendix A.1.1. This appendix also displays results obtained from the HP-filter with a smoothing parameter equal to 10^5 which is the value used by Shimer (2005) and Foote and Ryan (2015).

[6] The population aged 16 and over from which new unemployed entrants have been removed.

With regards to employment to population ratios by occupations, Table 2 shows that high skill employment is the least volatile and cyclical employment series while middle and low skill employment appear to share similar cyclical properties. All three employment series are positively correlated with GDP but their correlations are smaller than reported for aggregate employment.[7] For unemployment rates, it is worth pointing out the high volatility of high skill unemployment[8] despite the cyclical component of this series being the least correlated with GDP. Middle and low skill unemployment rates are strongly negatively correlated with GDP.

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$		σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Emp.					**Unemp.**				
Aggregate									
p^{EU}	0.069	4.772	-0.752	0.634	p^{UE}	0.080	5.494	0.818	0.822
p^{EI}	0.032	2.179	0.324	0.263	p^{UI}	0.057	3.899	0.800	0.749
High Skill									
$p^{E^hE^m}$	0.119	8.241	0.287	0.393	$p^{U^hE^h}$	0.113	7.808	0.511	0.494
$p^{E^hE^l}$	0.096	6.609	0.377	0.286	$p^{U^hE^m}$	0.156	10.753	0.544	0.306
$p^{E^hU^h}$	0.100	6.921	-0.632	0.531	$p^{U^hE^l}$	0.142	9.828	0.348	0.316
p^{E^hI}	0.057	3.908	0.031	-0.036	p^{U^hI}	0.084	5.826	0.565	0.359
Middle Skill									
$p^{E^mE^h}$	0.088	6.058	0.217	0.430	$p^{U^mE^h}$	0.161	11.105	0.456	0.274
$p^{E^mE^l}$	0.069	4.734	0.286	-0.020	$p^{U^mE^m}$	0.103	7.121	0.676	0.665
$p^{E^mU^m}$	0.088	6.060	-0.615	0.448	$p^{U^mE^l}$	0.099	6.807	0.561	0.400
p^{E^mI}	0.046	3.178	0.323	0.236	p^{U^mI}	0.059	4.098	0.706	0.490
Low Skill									
$p^{E^lE^h}$	0.101	6.967	0.446	0.465	$p^{U^lE^h}$	0.164	11.330	0.304	0.151
$p^{E^lE^m}$	0.053	3.673	0.226	-0.014	$p^{U^lE^m}$	0.131	9.064	0.731	0.593
$p^{E^lU^l}$	0.067	4.598	-0.717	0.572	$p^{U^lE^l}$	0.075	5.143	0.781	0.624
p^{E^lI}	0.038	2.599	0.237	0.079	p^{U^lI}	0.066	4.523	0.691	0.639
Inactivity									
Aggregate									
p^{IE}	0.043	2.992	0.655	0.391					
p^{IU}	0.064	4.439	-0.688	0.639					
Skill									
p^{IE^h}	0.071	4.916	0.247	-0.026					
p^{IE^m}	0.063	4.337	0.578	0.235					
p^{IE^l}	0.054	3.713	0.530	0.152					
p^{IU^h}	0.099	6.827	-0.438	0.254					
p^{IU^m}	0.078	5.381	-0.607	0.451					
p^{IU^l}	0.067	4.653	-0.608	0.537					

The cyclical component x_t is extracted as 100 times the log deviation from the HP-filter trend with smoothing parameter $\lambda = 1600$. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 3: Cyclical Properties for quarterly average of flow rates over the period 1976-2010

[7] It is worth noting that no restrictions ensure that the correlation for aggregate stocks is bounded by the correlations for disaggregated stocks. For instance, we can show that for series detrended in level (as in Tables 9 and 12 in Appendix A.1.1), the correlation for aggregate stocks is a weighted average of disaggregated stocks' correlations with the weight given by the relative standard deviation (e.g. $\rho_{E_t,y_t} = \frac{\sigma_{E^h}}{\sigma_E}\rho_{E^h_t,y_t} + \frac{\sigma_{E^m}}{\sigma_E}\rho_{E^m_t,y_t} + \frac{\sigma_{E^l}}{\sigma_E}\rho_{E^l_t,y_t}$). Since $\sigma_{E^h} + \sigma_{E^m} + \sigma_{E^l} > \sigma_E$, the sum of the weights is greater than 1 and the correlation for aggregate employment is bigger than for disaggregated series. This formula does not hold exactly when cycles are computed as log deviations from trends but the results in Table 2 suggest that a similar condition applies.

[8] This observation comes from the computation of the cyclical component in log (multiplicative model). When computed in level, the cyclical component is more volatile for the low skill unemployment rate. See Table 9 in Appendix A.1.1.

Table 3 displays the cyclical properties for quarterly average of monthly flow rates p_t^{ij} or the discrete time transition rate from state i to state j during month t. For aggregate flow rates, results are again very similar to what is reported by Fujita and Ramey (2009) and Krusell et al. (2017). Inflows to unemployment (EU and IU) are countercyclical, whereas outflows (UE and UI) are procyclical. This implies that during recessions, inflows increase and outflows decrease which both contribute to the increase in the unemployment rate. The procylicality of p^{UI} and the countercylicality of p^{IU} can be seen as counterintuitive as they imply that unemployed are more likely to stay in unemployment during recessions while inactive individuals are more likely to enter unemployment.

As pointed by Elsby et al. (2015), the procylicality of p^{UI} can be explained by a change in the composition of the unemployment pool during recessions. Workers more attached to the labor force (prime aged men) enter unemployment which lowers the aggregate exit rate to inactivity. On the other hand, the countercyclicality of p^{IU} can be explained by the Added Worker effect studied in detail by Mankart and Oikonomou (2016b).[9]. However, Elsby et al. (2015) argue that married couples with an inactive spouse only represent a small subset of the workforce and that the Added Worker effect alone, is probably not enough to fully explain the countercyclicality of p^{IU}. Furthermore, misclassification errors could affect the cyclical behavior of p^{IU} as Elsby et al. (2015) and Krusell et al. (2017) show that this transiton rate is much less countercyclical in the corrected data. Alternatively, time aggregation could also potentially explain the cyclicality of p^{IU} (and p^{IE}). In good times, transition from unemployment to employment are high and individuals transition faster through unemployment. The decrease in p^{IU} and the increase in p^{IE} could therefore result from a missed intermediate transition through unemployment. However, the adjustment applied in Ounnas (2019) corrects for this time aggregation problem and Elsby et al. (2015) argue that the adjusted transition rates preserve their cyclical properties.

With regard to occupation-specific transition rates, EU flow rates share similar cyclical properties across high, middle and low skill occupations.[10] Consistent with Fallick and Fleischman (2004), EE flow rates are mildly procyclical. Although, flow rates from unemployment are all procyclical, those involving high skill occupations (from and to) are usually less correlated with GDP. This observation also holds for flows from inactivity, in particular for the flow rate to high skill employment (p^{IE^h}). Flows to middle and low skill occupations seem to share relatively similar cyclical properties.

3 Variance Decomposition

I start this section by presenting the framework developed by Elsby et al. (2015) and used to decompose the variance of the fluctuations in stocks. This decomposition relates fluctuations[11] of stocks to variations in flow rates which then allows to compute the contributions of each flow rate to the variance of the stocks of interest. In a second step, I show how this framework for disaggregated stocks, $E_t^h, E_t^m, \ldots, U_t^l$, can be used to study fluctuations of aggregate stocks, E_t, U_t and lf_t. The last part of this section presents some minor adjustments to the procedure proposed by Elsby et al. (2015) that allow to slightly improve the contributions computed from the variance decomposition.

[9] The Added Worker effect captures the mechanism through which the spouse (usually the woman) may enter the labor force during recessions when the other spouse loses her/his job. This mechanism allows to ensure the household against income loss during these periods.

[10] As discussed for unemployment rates by occupations, the higher volatility of the $p^{E^hU^h}$ cyclical component comes from the extraction of this component as log deviations. See Table 12 in Appendix A.1.1.

[11] Throughout the paper, I use the terms "fluctuations", "changes" or "variations" to refer to the first difference in the series of interest (i.e. $\Delta x_t = x_t - x_{t-1}$).

3.1 Variance Decomposition's Framework

Elsby et al. (2015) start by assuming that monthly labor market stocks, s_t evolve according to a discrete time first order Markov chain (DTMC):[12]

$$\underbrace{\begin{bmatrix} E^h \\ E^m \\ E^l \\ U^h \\ U^m \\ U^l \\ I \end{bmatrix}_t}_{s_t} = \underbrace{\begin{bmatrix} p^{E^hE^h} & p^{E^mE^h} & p^{E^lE^h} & p^{U^hE^h} & p^{U^mE^h} & p^{U^lE^h} & p^{IE^h} \\ p^{E^hE^m} & p^{E^mE^m} & p^{E^lE^m} & p^{U^hE^m} & p^{U^mE^m} & p^{U^lE^m} & p^{IE^m} \\ p^{E^hE^l} & p^{E^mE^l} & p^{E^lE^l} & p^{U^hE^l} & p^{U^mE^l} & p^{U^lE^l} & p^{IE^l} \\ p^{E^hU^h} & p^{E^mU^h} & p^{E^lU^h} & p^{U^hU^h} & p^{U^mU^h} & p^{U^lU^h} & p^{IU^h} \\ p^{E^hU^m} & p^{E^mU^m} & p^{E^lU^m} & p^{U^hU^m} & p^{U^mU^m} & p^{U^lU^m} & p^{IU^m} \\ p^{E^hU^l} & p^{E^mU^l} & p^{E^lU^l} & p^{U^hU^l} & p^{U^mU^l} & p^{U^lU^l} & p^{IU^l} \\ p^{E^hI} & p^{E^mI} & p^{E^lI} & p^{U^hI} & p^{U^mI} & p^{U^lI} & p^{II} \end{bmatrix}_t}_{P_t} \underbrace{\begin{bmatrix} E^h \\ E^m \\ E^l \\ U^h \\ U^m \\ U^l \\ I \end{bmatrix}_{t-1}}_{s_{t-1}}$$

where the stocks, s_t, are normalized by total population. P_t is the discrete time transition matrix (or stochastic matrix) and p_t^{ij} is the flow rate from state i to state j. We have:

$$s_t = P_t s_{t-1}$$

$$\begin{aligned} p_t^{ij} &\geq 0 \\ p_t^{ii} &= 1 - \sum_{j \neq i} p_t^{ij} \end{aligned}$$

Using the fact that total population is normalized to 1, the above Markov chain can be rewritten as:

$$\underbrace{\begin{bmatrix} E^h \\ E^m \\ E^l \\ U^h \\ U^m \\ U^l \end{bmatrix}_t}_{\tilde{s}_t} = \underbrace{\begin{bmatrix} p^{E^hE^h} - p^{IE^h} & p^{E^mE^h} - p^{IE^h} & p^{E^lE^h} - p^{IE^h} & p^{U^hE^h} - p^{IE^h} & p^{U^mE^h} - p^{IE^h} & p^{U^lE^h} - p^{IE^h} \\ p^{E^hE^m} - p^{IE^m} & p^{E^mE^m} - p^{IE^m} & p^{E^lE^m} - p^{IE^m} & p^{U^hE^m} - p^{IE^m} & p^{U^mE^m} - p^{IE^m} & p^{U^lE^m} - p^{IE^m} \\ p^{E^hE^l} - p^{IE^l} & p^{E^mE^l} - p^{IE^l} & p^{E^lE^l} - p^{IE^l} & p^{U^hE^l} - p^{IE^l} & p^{U^mE^l} - p^{IE^l} & p^{U^lE^l} - p^{IE^l} \\ p^{E^hU^h} - p^{IU^h} & p^{E^mU^h} - p^{IU^h} & p^{E^lU^h} - p^{IU^h} & p^{U^hU^h} - p^{IU^h} & p^{U^mU^h} - p^{IU^h} & p^{U^lU^h} - p^{IU^h} \\ p^{E^hU^m} - p^{IU^m} & p^{E^mU^m} - p^{IU^m} & p^{E^lU^m} - p^{IU^m} & p^{U^hU^m} - p^{IU^m} & p^{U^mU^m} - p^{IU^m} & p^{U^lU^m} - p^{IU^m} \\ p^{E^hU^l} - p^{IU^l} & p^{E^mU^l} - p^{IU^l} & p^{E^lU^l} - p^{IU^l} & p^{U^hU^l} - p^{IU^l} & p^{U^mU^l} - p^{IU^l} & p^{U^lU^l} - p^{IU^l} \end{bmatrix}_t}_{\tilde{P}_t} \underbrace{\begin{bmatrix} E^h \\ E^m \\ E^l \\ U^h \\ U^m \\ U^l \end{bmatrix}_{t-1}}_{\tilde{s}_{t-1}} + \underbrace{\begin{bmatrix} p^{IE^h} \\ p^{IE^m} \\ p^{IE^l} \\ p^{IU^h} \\ p^{IU^m} \\ p^{IU^l} \end{bmatrix}_t}_{v_t} \quad (1)$$

or

$$\tilde{s}_t = \tilde{P}_t \tilde{s}_{t-1} + v_t \quad (2)$$

where $\tilde{P}_t$ is no longer a stochastic matrix.

Elsby et al. (2015) show that this process can be rewritten as the following partial adjustment equation:

$$\Delta \tilde{s}_t = A_t \Delta \bar{\tilde{s}}_t + B_t \Delta \tilde{s}_{t-1} \quad (3)$$

where $\bar{\tilde{s}}_t$ is the vector of steady state stocks and A_t and B_t are given by:

$$\begin{aligned} A_t &= I - \tilde{P}_t \\ B_t &= A_t \tilde{P}_{t-1} A_{t-1}^{-1} \\ \bar{\tilde{s}}_t &= A_t^{-1} v_t \end{aligned}$$

[12] Note that this assumption usually corresponds to how stocks evolve in standard search model of the labor market (e.g. search and matching model). Akerlof and Main (1981) discuss the limits of this assumption for the labor market.

Iterating backwards on (3) leads to:

$$\Delta\tilde{s}_t = \sum_{j=0}^{t-1}\prod_{i=0}^{j-1} B_{t-i}A_{t-j}\Delta\bar{\tilde{s}}_{t-j} + \prod_{j=0}^{t-1} B_{t-j}\Delta\tilde{s}_0 \tag{4}$$

Given some initial condition $\Delta\tilde{s}_0$, equation (4) implies that we can express the current variations in labor market stocks as the sum of current and past changes in their steady states.

In order to compute these steady state variations and to link them to flow rates, Elsby et al. (2015) propose to switch from a discrete to a continuous time framework. A continuous time Markov chain (CTMC) can be defined in the following way (Norris (1997)):

$$\dot{s} = F_t s_t \tag{5}$$

with F_t, the *infinitesimal generator* matrix of the CTMC satisfying:

$$\begin{aligned} &0 \leq -f_t^{ii} \leq \infty \\ &f_t^{ij} \geq 0 \\ &\sum_j f_t^{ij} = 0 \end{aligned}$$

In the context of this paper, the generator matrix has the following form:

$$F_t = \begin{bmatrix} f^{E^h} & f^{E^mE^h} & f^{E^lE^h} & f^{U^hE^h} & f^{U^mE^h} & f^{U^lE^h} & f^{IE^h} \\ f^{E^hE^m} & f^{E^m} & f^{E^lE^m} & f^{U^hE^m} & f^{U^mE^m} & f^{U^lE^m} & f^{IE^m} \\ f^{E^hE^l} & f^{E^mE^l} & f^{E^l} & f^{U^hE^l} & f^{U^mE^l} & f^{U^lE^l} & f^{IE^l} \\ f^{E^hU^h} & 0 & 0 & f^{U^h} & 0 & 0 & f^{IU^h} \\ 0 & f^{E^mU^m} & 0 & 0 & f^{U^m} & 0 & f^{IU^m} \\ 0 & 0 & f^{E^lUl} & 0 & 0 & f^{U^l} & f^{IU^l} \\ f^{E^hI} & f^{E^mI} & f^{E^lI} & f^{U^hI} & f^{U^mI} & f^{U^lI} & f^{I} \end{bmatrix}_t \tag{6}$$

where f^i can be interpreted as the staying rate in state i, and f^{ij} are instantaneous transition rates (hazard rates) from state i to j. Note that some hazard rates have to be restricted to 0 since it is impossible to transition instantaneously between some states. These restrictions originate from the fact that the occupation of an unemployed is assigned according to her previous occupation in employment. Therefore, instantaneous transition rates such as $f^{E^hU^m}$ or $f^{U^hU^m}$, should be equal to 0.

The CTMC can also be reduced and expressed as:

$$\dot{\tilde{s}} = \tilde{F}_t\tilde{s}_t + q_t$$

$\tilde{F}_t$ and q_t can be obtained in a similar manner as $\tilde{P}_t$ and v_t in (1). The steady state is given by:

$$\bar{\tilde{s}}_t = -\tilde{F}_t^{-1}q_t \tag{7}$$

and taking a first order approximation of the steady state stocks (7) around lagged values of hazard rates leads to:

$$\Delta\bar{\tilde{s}}_t \approx \sum_i\sum_{j\neq i}\frac{\partial\bar{\tilde{s}}_t}{\partial f_t^{ij}}\Delta f_t^{ij} \tag{8}$$

where the steady states derivatives with respect to each hazard rate can be obtained from results in matrix algebra (see Petersen and Pedersen (2012)). Therefore, (8) allows to compute the steady state variations $\Delta\bar{\tilde{s}}_t^{ij}$ originating from variations of each hazard rate f_t^{ij}. For instance, fluctuations of $f_t^{E^hU^h}$ imply:

$$\begin{aligned}\Delta\bar{\tilde{s}}_t^{E^hU^h} &\approx \frac{\partial\bar{\tilde{s}}_t}{\partial f_t^{E^hU^h}}\Delta f_t^{E^hU^h} \\ &\approx \tilde{F}_t^{-1}\frac{\partial\tilde{F}_t}{\partial f_t^{E^hU^h}}\tilde{F}_t^{-1}q_t\Delta f_t^{E^hU^h}\end{aligned}$$

using (7) and the identity for the derivative of matrix inverse. This approximation is key and allows to connect fluctuations of hazard rates and stocks. More precisely, variations of hazard rates Δf_t^{ij}, affect the steady states stocks, $\Delta\bar{\tilde{s}}_t$, which drives the current fluctuations of stocks, $\Delta\tilde{s}_t$ (through equation (3)). We then have:

$$var(\Delta\tilde{s}_t) \approx cov\left(\Delta\tilde{s}_t, \sum_{j=0}^{t-1}\prod_{i=0}^{j-1}B_{t-i}A_{t-j}\sum_i\sum_{j\neq i}\frac{\partial\bar{\tilde{s}}_{t-j}}{\partial f_{t-j}^{ij}}\Delta f_{t-j}^{ij}\right) \tag{9}$$

for a given stock (e.g. E_t^h), the contribution of a specific hazard rate f^{ij} is obtained as:

$$\beta_{E^h}^{ij} = \frac{cov\left(\Delta E_t^h, \sum_{j=0}^{t-1}\prod_{i=0}^{j-1}B_{t-i}A_{t-j}\frac{\partial\bar{E}_t^h}{\partial f_t^{ij}}\Delta f_t^{ij}\right)}{var\left(\Delta E_t^h\right)} \tag{10}$$

The quantities in the vector $\tilde{s}_t$ are normalized by total population while the interest is in the variance of the unemployment rate (e.g. $u_t^h = \frac{U_t^h}{L_t^h}$ with $L_t^h = E_t^h + U_t^h$). Taking a first order approximation of the unemployment rate first difference around lagged values of E and U leads to:

$$\Delta u_t \approx (1-u_{t-1})\frac{\Delta U_t}{L_{t-1}} + u_{t-1}\frac{\Delta E_t}{L_{t-1}} \tag{11}$$

with $\Delta U_t = \Delta U_t^h + \Delta U_t^m + \Delta U_t^l$ and $\Delta E_t = \Delta E_t^h + \Delta E_t^m + \Delta E_t^l$. This expression also applies to unemployment rates by occupations. We can then compute the contribution of the hazard rate f_t^{ij} as:

$$\Delta u_t^{ij} \approx (1-u_{t-1})\frac{\Delta U_t^{ij}}{L_{t-1}} + u_{t-1}\frac{\Delta E_t^{ij}}{L_{t-1}} \tag{12}$$

where $\Delta U_t^{ij} = \Delta U_t^{h,ij} + \Delta U_t^{m,ij} + \Delta U_t^{l,ij}$ and $\Delta E_t^{ij} = \Delta E_t^{h,ij} + \Delta E_t^{m,ij} + \Delta E_t^{l,ij}$. $\Delta U_t^{k,ij}$ and $\Delta E_t^{k,ij}$ are the k occupation group (un)-employment fluctuations originating from the hazard rate f_t^{ij}.

There are six states in the vector $\Delta\tilde{s}_t$ and 30 hazard rates f_t^{ij}. Defining $\Delta\tilde{s}_t^{ij}$ to be the contribution of the hazard rate f_t^{ij} to the fluctuations of stocks, there is a total of 180 contributions $\Delta\tilde{s}_t^{ij}$ to compute. Using equation (8), we can compute the steady states variations for each hazard rate, $\Delta\bar{\tilde{s}}_t^{ij}$. For some initial values $\Delta\tilde{s}_0^{ij}$, equation (3) can be used to produce fluctuations of stocks resulting from each individual hazard rates:

$$\Delta\tilde{s}_t^{ij} = A_t\Delta\bar{\tilde{s}}_t^{ij} + B_t\Delta\tilde{s}_{t-1}^{ij} \tag{13}$$

and the fluctuations, $\Delta\tilde{s}_t$, are obtained by adding up each hazard rate contributions:

$$\Delta\tilde{s}_t = Z\Delta\tilde{s}_t^{ij} \tag{14}$$

where Z is a 6×180 matrix of 0 and 1 which sums the relevant contributions.[13] Once these contributions have been obtained, results in terms of unemployment rates are computed using the approximation (12). This process is applied to monthly data and quarterly results are then computed by taking monthly average of stocks. Defining months $1, 2$ and 3 of quarter t, the quarterly variations, Δu_t, are related to monthly variations through:

$$\Delta u_t = \frac{\Delta u_{t-1,2} + 2\Delta u_{t-1,3} + 3\Delta u_{t,1} + 2\Delta u_{t,2} + \Delta u_{t,3}}{3}$$

and the quarterly unemployment rate fluctuation originating from the variations of hazard rate f_t^{ij}, Δu_t^{ij}, is given by:

$$\Delta u_t^{ij} = \frac{\Delta u_{t-1,2}^{ij} + 2\Delta u_{t-1,3}^{ij} + 3\Delta u_{t,1}^{ij} + 2\Delta u_{t,2}^{ij} + \Delta u_{t,3}^{ij}}{3} \tag{15}$$

3.2 Variance Decomposition for Aggregate Stocks

In order to study the fluctuations of the aggregate unemployment rate, it is possible to use the contributions $\Delta\tilde{s}_t^{ij}$ computed from the disaggregated Markov Chain and equation (12). Likewise for the labor force participation rate using the fact that $\Delta \mathrm{lf}_t = \Delta E_t^h + \Delta E_t^m + \cdots + \Delta U_t^l$. However, an alternative way to proceed is to directly compute aggregate stocks from the CTMC defined in (5). More precisely, it holds that:

$$\begin{aligned}
\dot{E} &= \dot{E}^h + \dot{E}^m + \dot{E}^l \\
\dot{U} &= \dot{U}^h + \dot{U}^m + \dot{U}^l
\end{aligned}$$

and from (5), one has:

$$\begin{aligned}
\dot{E} = {} & f_t^{E^h} E_t^h + f_t^{E^m E^h} E_t^m + f_t^{E^l E^h} E_t^l + f_t^{U^h E^h} U_t^h + f_t^{U^m E^h} U_t^m + f_t^{U^l E^h} U_t^l + f_t^{IE^h} I_t \\
& + f_t^{E^h E^m} E_t^h + f_t^{E^m} E_t^m + f_t^{E^l E^m} E_t^l + f_t^{U^h E^m} U_t^h + f_t^{U^m E^m} U_t^m + f_t^{U^l E^m} U_t^l + f_t^{IE^m} I_t \\
& + f_t^{E^h E^l} E_t^h + f_t^{E^m E^l} E_t^m + f_t^{E^l} E_t^l + f_t^{U^h E^l} U_t^h + f_t^{U^m E^l} U_t^m + f_t^{U^l E^l} U_t^l + f_t^{IE^l} I_t
\end{aligned}$$

rearranging this expression leads to:

$$\begin{aligned}
\dot{E} = {} & \left(\left(f_t^{E^h} + f_t^{E^h E^m} + f_t^{E^h E^l} \right) \frac{E_t^h}{E_t} + \left(f_t^{E^m E^h} + f_t^{E^m} + f_t^{E^m E^l} \right) \frac{E_t^m}{E_t} + \left(f_t^{E^l E^h} + f_t^{E^l E^m} + f_t^{E^l} \right) \frac{E_t^l}{E_t} \right) E_t \\
& + \left(\left(f_t^{U^h E^h} + f_t^{U^h E^m} + f_t^{U^h E^l} \right) \frac{U_t^h}{U_t} + \left(f_t^{U^m E^h} + f_t^{U^m E^m} + f_t^{U^m E^l} \right) \frac{U_t^m}{U_t} + \left(f_t^{U^l E^h} + f_t^{U^l E^m} + f_t^{U^l E^l} \right) \frac{U_t^l}{U_t} \right) U_t \\
& + \left(f_t^{IE^h} + f_t^{IE^m} + f_t^{IE^l} \right) I_t
\end{aligned}$$

and I can define the following aggregate hazard rates f^E, f^{UE} and f^{IE}:

$$f_t^E = \left(f_t^{E^h} + f_t^{E^h E^m} + f_t^{E^h E^l} \right) \frac{E_t^h}{E_t} + \left(f_t^{E^m E^h} + f_t^{E^m} + f_t^{E^m E^l} \right) \frac{E_t^m}{E_t} + \left(f_t^{E^l E^h} + f_t^{E^l E^m} + f_t^{E^l} \right) \frac{E_t^l}{E_t} \tag{16}$$

[13] The 180×1 vector of contributions, $\Delta\tilde{s}_t^{ij}$ is such that, the first six elements of this vector are the contributions of the $f_t^{E^h E^m}$ hazard rate to the fluctuations of the 6 stocks ordered as in (1). The next six elements are the contributions of $f_t^{E^h E^l}$, the following six are the contributions of $f_t^{E^h U^h}$ ... This implies that the 6×180 matrix Z is made of 30 identity matrices of size 6×6.

$$
\begin{aligned}
f_t^{UE} &= \left(f_t^{U^hE^h} + f_t^{U^hE^m} + f_t^{U^hE^l}\right)\frac{U_t^h}{U_t} + \left(f_t^{U^mE^h} + f_t^{U^mE^m} + f_t^{U^mE^l}\right)\frac{U_t^m}{U_t} \\
&\quad + \left(f_t^{U^lE^h} + f_t^{U^lE^m} + f_t^{U^lE^l}\right)\frac{U_t^l}{U_t} && (17) \\
f_t^{IE} &= f_t^{IE^h} + f_t^{IE^m} + f_t^{IE^l} && (18)
\end{aligned}
$$

similar steps for unemployment and inactivity lead to the following aggregate hazard rates:

$$
\begin{aligned}
f_t^{EU} &= f_t^{E^hU^h}\frac{E_t^h}{E_t} + f_t^{E^mU^m}\frac{E_t^m}{E_t} + f_t^{E^lU^l}\frac{E_t^l}{E_t} && (19) \\
f_t^{U} &= f_t^{U^h}\frac{U_t^h}{U_t} + f_t^{U^m}\frac{U_t^m}{U_t} + f_t^{U^l}\frac{U_t^l}{U_t} && (20) \\
f_t^{IU} &= f_t^{IU^h} + f_t^{IU^m} + f_t^{IU^l} && (21) \\
f_t^{EI} &= f_t^{E^hI}\frac{E_t^h}{E_t} + f_t^{E^mI}\frac{E_t^m}{E_t} + f_t^{E^lI}\frac{E_t^l}{E_t} && (22) \\
f_t^{UI} &= f_t^{U^hI}\frac{U_t^h}{U_t} + f_t^{U^mI}\frac{U_t^m}{U_t} + f_t^{U^lI}\frac{U_t^l}{U_t} && (23)
\end{aligned}
$$

Using these aggregate hazard rates, I can analyze aggregate stocks fluctuations in the usual 3-states framework studied by Elsby et al. (2015):

$$
\begin{bmatrix} \dot{E} \\ \dot{U} \\ \dot{I} \end{bmatrix} = \begin{bmatrix} f^{E} & f^{UE} & f^{IE} \\ f^{EU} & f^{U} & f^{IU} \\ f^{EI} & f^{UI} & f^{I} \end{bmatrix}_t \begin{bmatrix} E \\ U \\ I \end{bmatrix}_t
$$

which can be reduced to:

$$
\begin{bmatrix} \dot{E} \\ \dot{U} \end{bmatrix} = \begin{bmatrix} -f^{EU} - f^{EI} - f^{IE} & f^{UE} - f^{IE} \\ f^{EU} - f^{IU} & -f^{UE} - f^{UI} - f^{IU} \end{bmatrix}_t \begin{bmatrix} E \\ U \end{bmatrix}_t + \begin{bmatrix} f^{IE} \\ f^{IU} \end{bmatrix}_t
$$

Therefore, these computations allow to reduce the dimension of the Markov Chain from 7 to 3 states (from 6 to 2 for the reduced Markov Chain) and to trace the effect of disaggregated hazard rates by occupations on aggregate stocks through their impact on aggregate transition rates.
Furthermore, the fluctuations of aggregate hazard rates can be decomposed into a compositional effect and an hazard rate effect. For instance, fluctuations of the aggregate employment to unemployment hazard rate can be written as:

$$
\begin{aligned}
\Delta f_t^{EU} &= f_t^{E^hU^h}\frac{E_t^h}{E_t} + f_t^{E^mU^m}\frac{E_t^m}{E_t} + f_t^{E^lU^l}\frac{E_t^l}{E_t} - \left(f_{t-1}^{E^hU^h}\frac{E_{t-1}^h}{E_{t-1}} + f_{t-1}^{E^mU^m}\frac{E_{t-1}^m}{E_{t-1}} + f_{t-1}^{E^lU^l}\frac{E_{t-1}^l}{E_{t-1}}\right) \\
&= \underbrace{f_{t-1}^{E^hU^h}\Delta\frac{E_t^h}{E_t} + f_{t-1}^{E^mU^m}\Delta\frac{E_t^m}{E_t} + f_{t-1}^{E^lU^l}\Delta\frac{E_t^l}{E_t}}_{\text{Compositional effect}} + \underbrace{\Delta f_t^{E^hU^h}\frac{E_t^h}{E_t} + \Delta f_t^{E^mU^m}\frac{E_t^m}{E_t} + \Delta f_t^{E^lU^l}\frac{E_t^l}{E_t}}_{\text{Hazard rate effect}} \\
&= \underbrace{(f_{t-1}^{E^mU^m} - f_{t-1}^{E^hU^h})\Delta\frac{E_t^m}{E_t} + (f_{t-1}^{E^lU^l} - f_{t-1}^{E^hU^h})\Delta\frac{E_t^l}{E_t}}_{\text{Compositional effect}} + \underbrace{\Delta f_t^{E^hU^h}\frac{E_t^h}{E_t} + \Delta f_t^{E^mU^m}\frac{E_t^m}{E_t} + \Delta f_t^{E^lU^l}\frac{E_t^l}{E_t}}_{\text{Hazard rate effect}} \\
&= \underbrace{\sum_{i=\{m,l\}} (f_{t-1}^{E^iU^i} - f_{t-1}^{E^hU^h})\Delta\frac{E_t^i}{E_t}}_{\text{Compositional effect}} + \underbrace{\sum_{i=\{h,m,l\}} \Delta f_t^{E^iU^i}\frac{E_t^i}{E_t}}_{\text{Hazard rate effect}} && (24)
\end{aligned}
$$

where to pass from the first to second line, I add and subtract $f_{t-1}^{E^iU^i}\frac{E_t^i}{E_t}$ and I use the fact that $\Delta\frac{E_t^h}{E_t} = -\Delta\frac{E_t^m}{E_t} - \Delta\frac{E_t^l}{E_t}$. The compositional effect captures variations of aggregate hazard rates originating from fluctuations in the occupational shares of employment (or unemployment for aggregate transition rates from this state). For example, when the middle and low skill employment shares increase, the aggregate hazard rate f_t^{EU} tends to increase given that $f_t^{E^lU^l}$ and $f_t^{E^mU^m}$ are (on average) greater than $f_t^{E^hU^h}$. Similar expression can be derived for the remaining hazard rates from employment and unemployment. No compositional effect can be derived for transition rates from inactivity given that no occupation is assigned to individual outside of the labor force. Using these aggregate hazard rates fluctuations, I can apply the same steps described in Section 3.1. I can compute steady state fluctuations using (8) with $\tilde{s}_t = [E_t\ U_t]'$ and generate fluctuations in aggregate stocks from each specific hazard rate using (13).

I proceed in the same way for labor force participation with $\dot{\text{lf}} = \dot{E} + \dot{U}$. I then have the following 2 states framework:

$$\begin{bmatrix} \dot{\text{lf}} \\ \dot{I} \end{bmatrix} = \begin{bmatrix} f^{\text{lf}} & f^{I\text{lf}} \\ f^{\text{lf}I} & f^{I} \end{bmatrix}_t \begin{bmatrix} \text{lf} \\ I \end{bmatrix}_t$$

This 2 states Markov Chain reduces to the following single equation:

$$\dot{\text{lf}} = -(f^{\text{lf}I} + f^{I\text{lf}})\text{lf}_t + f^{I\text{lf}}$$

with

$$\begin{aligned} f_t^{I\text{lf}} &= f_t^{IE} + f_t^{IU} \\ f_t^{\text{lf}I} &= f_t^{EI}\frac{E_t}{\text{lf}_t} + f_t^{UI}\frac{U_t}{\text{lf}_t} \end{aligned}$$

where the hazard rates f^{IE}, f^{IU}, f^{EI} and f^{UI} are given in equations (18) and (21)-(23).

The fluctuations of the hazard rate from the labor force to inactivity, f_t^{lfI}, can also be decomposed between a compositional and an hazard rate effect:

$$\Delta f_t^{\text{lf}I} = f_{t-1}^{EI}\Delta\frac{E_t}{\text{lf}_t} + f_{t-1}^{UI}\Delta\frac{U_t}{\text{lf}_t} + \Delta f_t^{EI}\frac{E_t}{\text{lf}_t} + \Delta f_t^{UI}\frac{U_t}{\text{lf}_t} \tag{25}$$

this expression can be further developed using $\Delta\frac{E_t}{\text{lf}_t} = -\frac{U_t}{\text{lf}_t}$ and the fluctuations Δf_t^{EI} and Δf_t^{UI} (which are similar to (24)):

$$\begin{aligned} \Delta f_t^{\text{lf}I} = {} & \underbrace{(f_t^{UI} - f_t^{EI})\Delta\frac{U_t}{\text{lf}_t}}_{\text{Compositional effect (1)}} + \underbrace{\sum_{i=\{m,l\}} \frac{E_t}{\text{lf}_t}\left(f_{t-1}^{E^iI} - f_{t-1}^{E^hI}\right)\Delta\frac{E_t^i}{E_t} + \frac{U_t}{\text{lf}_t}\left(f_{t-1}^{U^iI} - f_{t-1}^{U^hI}\right)\Delta\frac{U_t^i}{U_t}}_{\text{Compositional effect (2)}} \\ & + \underbrace{\sum_{i=\{h,m,l\}} \frac{E_t^i}{\text{lf}_t}\Delta f_t^{E^iI} + \frac{U_t^i}{\text{lf}_t}\Delta f_t^{U^iI}}_{\text{Hazard rate effect}} \end{aligned} \tag{26}$$

This expression shows that there are two compositional effects. The second one is similar to the effect describe previously for aggregate (un)-employment. It captures variations in the occupational composition of employment and unemployment which affect the aggregate outflows to inactivity, f_t^{EI} and f_t^{UI} and therefore $f_t^{\text{lf}I}$. On the other hand, the first compositional effect in the above expression captures changes of the labor force composition between employment and unemployment. When the unemployment rate increases $\Delta\frac{U_t}{\text{lf}_t} > 0$, the outflow rate to inactivity increases given that $f_t^{UI} - f_t^{EI} > 0$. This effect is described by Barnichon (2019) while Elsby et al. (2019) emphasize the role played by hazard rates between employment and unemployment, f_t^{EU} and f_t^{UE} (which they label Churning). These two hazard rates do not explicitly appear in the above expression but their main effects act through the variations in the unemployment rate.[14]

3.3 A Small Adjustment

The decision to adjust the procedure described in the previous section comes from the fact that the fluctuations obtained from equation (3) and from (13) do not allow to exactly reproduce the observed fluctuations of stocks. This is highlighted in Figure 1 which illustrates, for example, that the fluctuations of high skill employment obtained from (3) explain around 92% of the variance in observed fluctuations.[15] For the other stocks, the observed fluctuations are actually matched fairly well by the recursion in (3), as the covariances between these two quantities lie between 98% and 103%.

The main idea of the adjustment is to augment the partial adjustment equation (13) with an error term $\tilde{\varepsilon}_t^{ij}$:

$$\Delta\tilde{s}_t^{ij} = A_t\Delta\bar{s}_t^{ij} + B_t\Delta\tilde{s}_{t-1}^{ij} + \tilde{\varepsilon}_t^{ij}, \qquad \tilde{\varepsilon}_t^{ij} \sim \mathcal{N}(0,\sigma_i^2) \tag{27}$$

these error terms can be seen as capturing measurement noise from approximations taken at various steps of the decomposition procedure, in particular (8) which computes steady state changes. The inclusion of this error term implies that we can use the Kalman Filter[16] to compute the contributions:

$$y_t = Z\alpha_t \tag{28}$$

$$\alpha_{t+1} = \mu_t + T_t\alpha_t + \eta_t, \qquad \eta_t \sim \mathcal{N}\left(0,\Sigma\right) \tag{29}$$

The observation vector y_t contains the observed fluctuations $\Delta\tilde{s}_t$ and Z is a matrix of 0 and 1 which sums the relevant contributions from the state vector (see (14)). The individual hazard rates contributions $\Delta\tilde{s}_t^{ij}$ are assumed to be the unobserved state variables in the vector α_t. Since there are 180 contributions to compute, the size of the state vector is 180×1 with $\mu_t = I_{30} \otimes A_t\Delta\bar{\tilde{s}}_t^{ij}$, $T_t = I_{30} \otimes B_t$ and η_t is the vector of error terms $\tilde{\varepsilon}_t^{ij}$.[17]

The Kalman filter allows to sequentially compute the conditional expectation ($E\left(\alpha_t|y_t\right) = a_t$) and variance ($Var\left(\alpha_t|y_t\right) = V_t$) of the state vector. For some initial values a_0 and V_0 and starting from the first period in the sample, the recursion produces a forecast of the observed variable y_t using (28). In a second step, the filter uses the observed realization of y_t to update the current state vector. It is this second step that allows to improve the results for individual contributions $\Delta\tilde{s}_t^{ij}$ compared to those obtained through the recursion (13).[18]

The use of the Kalman Filter also provides guidance on how to initialize the recursions and offers the possibility to estimate the variance parameters σ_i^2. Regarding initialization, it is common to start the recursion from the unconditional mean and variance of the state vector which can be computed from the state equation (29). However, these two quantities cannot easily be computed in the context of this work (since the matrix T_t is time dependent). As a result, I use the *exact initial Kalman Filter*

[14] Note that the emphasis is on the outflows from the labor force $f_t^{\text{lf}I}$ but it is also possible to study the staying rate f^{lf} since $f^{\text{lf}} = -f_t^{\text{lf}I}$. We have $f_t^{\text{lf}} = \left(f_t^E + f_t^{EU}\right)\frac{E_t}{\text{lf}_t} + \left(f_t^{UE} + f_t^U\right)\frac{U_t}{\text{lf}_t}$ which shows that f_t^{EU} and f_t^{UE} also have an effect on the staying rate. Note that these 2 hazard rates only partly explain the fluctuations of the staying rate which is also affected by the staying rate in employment and unemployment, f_t^E and f_t^U.

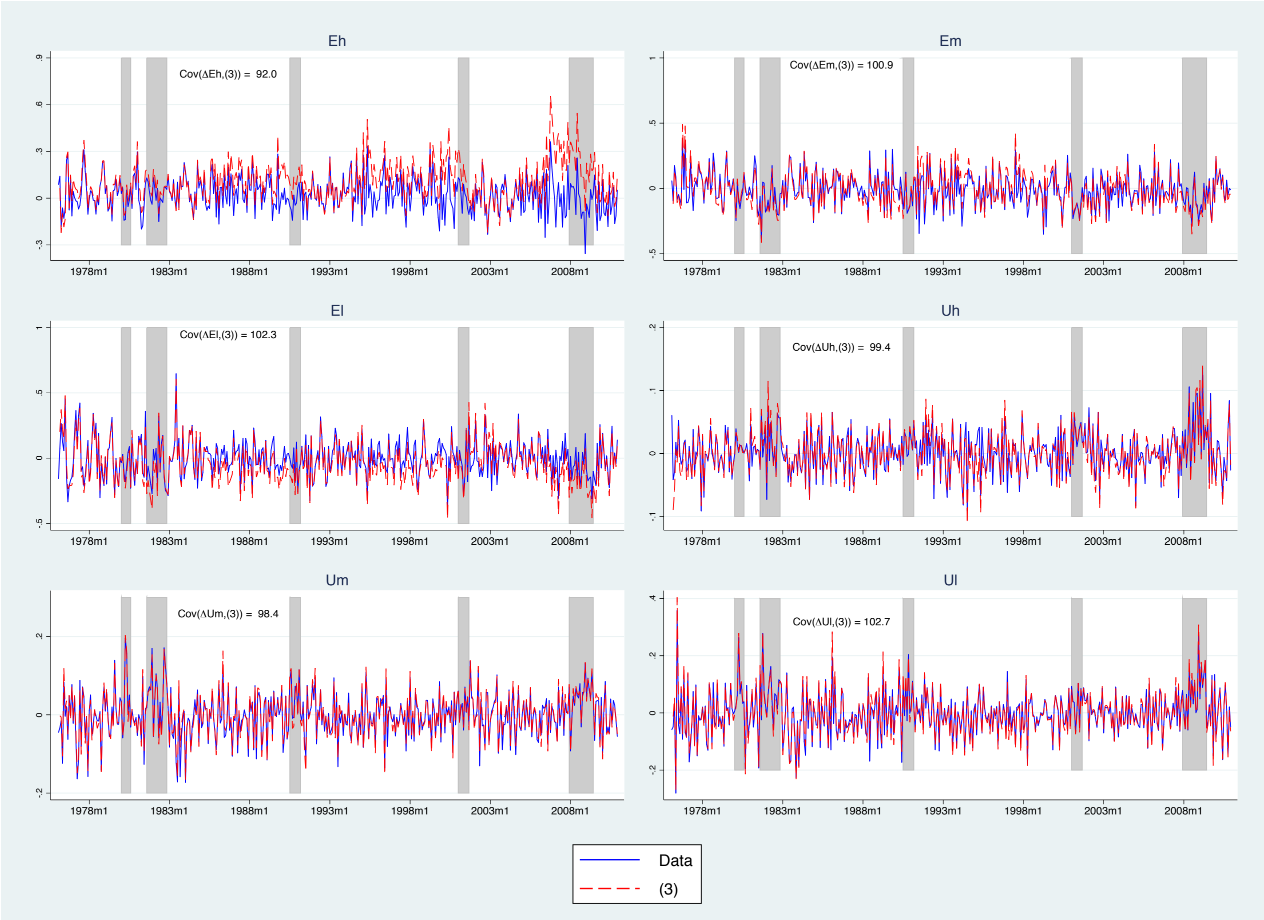
[15] Moreover, Figure 2 (and Figure 5 in Appendix A.2) shows that the stocks in levels generated from these fluctuations are quite different from the actual ones.

[16] See Durbin and Koopman (2012) for a detailed review of the Kalman Filter.

[17] The dimensions of these vectors and matrices apply to disaggregated stocks. For aggregate employment and unemployment there are 32 contributions (24 from hazard rates and 8 from compositional effects) and 64 in total for both stocks. The size of state vector is 64×1, A_t and B_t are 2×2 matrices, $\mu_t = I_{32} \otimes A_t\Delta\bar{s}_t^{ij}$, $T_t = I_{32} \otimes B_t$. Labor force participation is studied through a single equation and there are 17 contributions (12 from hazard rates f^{EI}, f^{UI}, f^{IE} and f^{IU} by occupations, 4 from occupation compositional effects and 1 for the compositional effect through the unemployment rate).

[18] Note that the results obtained through equation (13) can be obtained using the Kalman Filter by skipping the updating step as if y_t was missing.

of Durbin and Koopman (2012).[19]

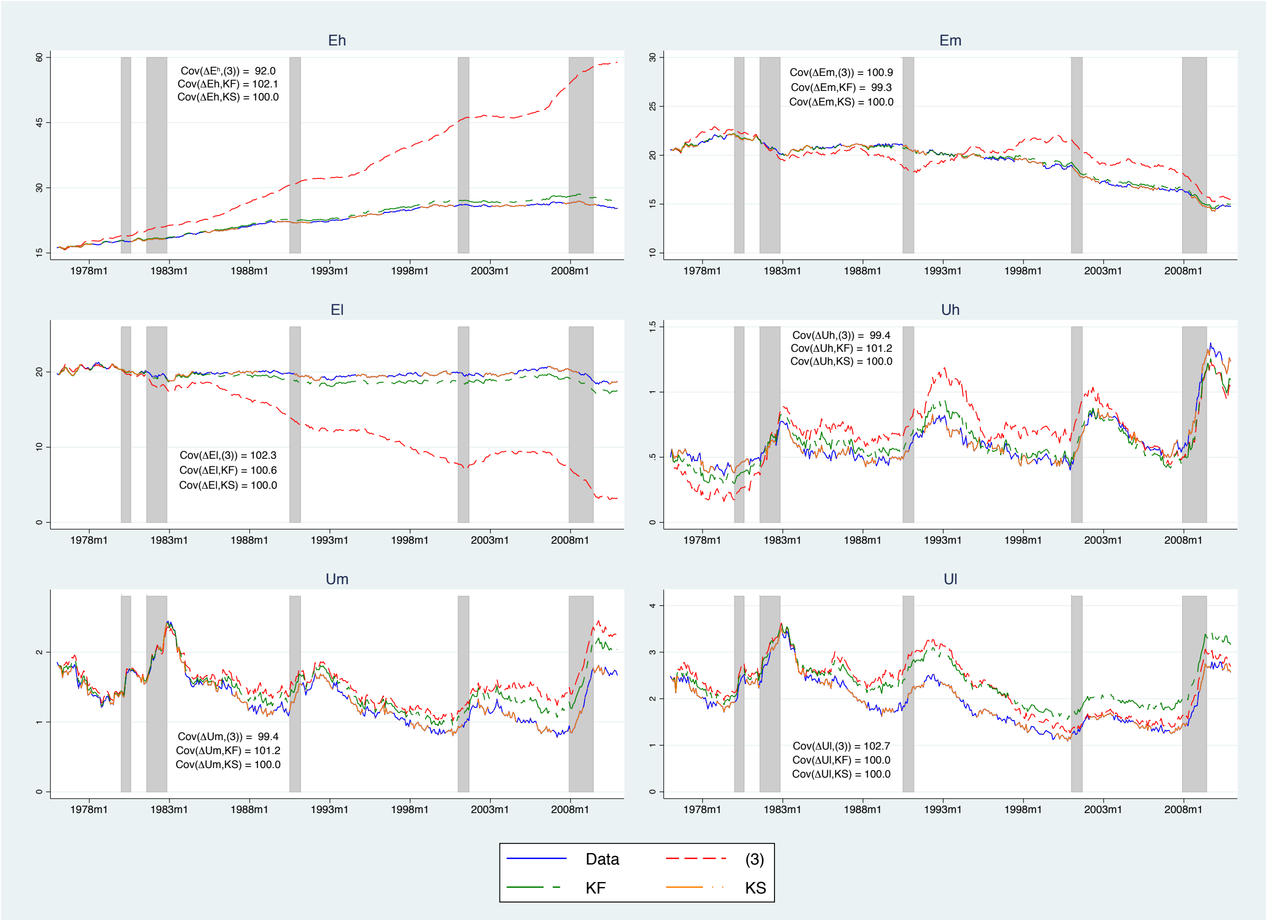


Comparison of the first difference in stock series obtained using recursion (3) in red with their data counterparts in blue. First difference are measured in percentages points.

Figure 1: First Difference of Stocks Series from Data and Recursion (3)

Figure 2 clearly sets out that the contributions obtained from the Kalman Filter better reproduce the evolution of stocks in level. Moreover, it is possible to further improve the fit through the use of the Kalman Smoother (see Durbin and Koopman (2012)). The Kalman Smoother recursions compute the expected value of the state vector given all the information available in the sample. As can be seen from Figure 2, the contributions computed from the smoothing recursions allow to (almost) perfectly match the evolution of stocks and therefore reproduce the actual fluctuations of these stocks. In Tables 13 and 14 in Appendix A.2, I also show that the contributions obtained from the Kalman Filter or Smoother only lead to marginal changes in the variance decomposition results. This could have been expected since the original contributions obtained through equation (13) were already reproducing fluctuations in stocks rather accurately (see Figure 1). Therefore, the main advantages of the Filter and Smoother adjustment are that they provide the ability to better reproduce the fluctuations of stocks in level as well as provide guidance on how to initialize the recursions.

[19] All the derivations and results as well as alternatives solution to tackle the issue of initialization, can be found in Durbin and Koopman (2012).



Comparison of stocks obtained from recursion (3) in red, from the Kalman Filter in green and from the Kalman Smoother in orange. Stocks are measure in percentages.

Figure 2: Effects of the Kalman Filter and Smoother Adjustment

From this point onwards, I work with contributions $\Delta\tilde{s}_t^{ij}$ obtained from the Kalman Smoother. Since these contributions are (almost) exact, I avoid using the approximation (12) to obtain contributions in terms of unemployment rates. Instead, these contributions can be computed as:

$$\begin{aligned}
\Delta u_t &= \frac{U_t}{L_t} - \frac{U_{t-1}}{L_{t-1}} \\
&= \frac{U_t L_{t-1} - U_{t-1} L_t}{L_t L_{t-1}} \\
&= \frac{\left(U_{t-1} + \Delta U_t\right) L_{t-1} - U_{t-1}\left(L_{t-1} + \Delta E_t + \Delta U_t\right)}{L_t L_{t-1}} \\
&= (1 - u_{t-1}) \frac{\Delta U_t}{L_t} + u_{t-1} \frac{\Delta E_t}{L_t}
\end{aligned}$$

Contributions for individual hazard rates f_t^{ij} can be computed from:

$$\Delta u_t^{ij} = (1 - u_{t-1}) \frac{\Delta U_t^{ij}}{L_t} + u_{t-1} \frac{\Delta E_t^{ij}}{L_t} \tag{30}$$

Note that this expression is very similar to the first order approximation (12) except for the denominator, which is the current labor force level instead of the previous period one. Quarterly contributions are then obtained using (15).

4 Results

This section presents the results obtained from the decomposition of quarterly fluctuations of unemployment and labor force participation rates. Section 4.1 discusses the results for occupation-specific unemployment rates whereas Sections 4.2 and 4.3 focus respectively, on the aggregate unemployment rate and the labor force participation rate. To facilitate the analysis, the contributions have been aggregated along various dimensions and the detailed results can be found in Table 15 in Appendix A.3.1.

4.1 Occupation-specific unemployment rates

Table 4 displays the results obtained from the variance decomposition of disaggregated unemployment rates quarterly fluctuations. The main take away from this table can be seen from panel (a) which aggregate hazard rates contributions in terms of ins and outs of unemployment. These results show that fluctuations of the high skill unemployment rate are mostly driven by hazard rates to unemployment (54.0%) while variations of the low skill unemployment rates are explained primarily by hazard rates out of unemployment (60.3%). The dynamics of the middle skill unemployment rate lies between these two occupation groups with ins and outs contributing for respectively, 39.7% and 53.3% of the variance. This heterogeneity across high, middle and low skill unemployment rates suggests that the occupational composition of the unemployment pool can affect the dynamics of the aggregate unemployment rate.[20]

The results from panel (a) also show that ins and outs account for almost the entirety of the variance of these unemployment rates with total contributions ranging from 93.0% (39.7%+53.3%) for the middle skill unemployment rate to 100.4% for the high skill one. The remaining hazard rates (from and to employment and between employment and inactivity) only contribute marginally to short term fluctuations of these various rates. Furthermore, variations in the unemployment rate of an occupation group are almost only explained by hazard rates in and out of of this specific occupation group. For example, ins and outs of high skill unemployment account for 100.8%, 1.0% and -0.8% of the variance of high, middle and low skill unemployment, respectively.

Panel (b) in Table 4 allows to better understand the heterogeneity in flows driving the dynamics of occupational unemployment rates. The inflow from employment to unemployment has relatively similar contributions for high and middle skill unemployment and slightly lower for low skill unemployment (respectively 28.1%, 28.8% and 23.9%). It is the inflow from inactivity that explains the difference across occupation groups. Table 4 shows that f^{IU} account for 25.9% of the high skill unemployment rate variance but only 10.9% and 9.3% for middle and low skill unemployment.

With regards to outflows from unemployment, the larger contribution of outs to low skill unemployment fluctuations originates from outflows to employment. These hazard rates explain 41.2% of the low skill unemployment rate variations against 30.5% and 32.2% for the high and middle skill unemployment rates. Note also that transition rates from unemployment to employment of a different skill level ($\Delta\tilde{s}^{U^iE^j}$) accounts for 8.5% to 16.3% of unemployment rates variances, and that these contributions appear to be increasing with the skill level (16.3% for high skills and 8.5% for low skills). Finally, outflows to inactivity explain a slightly higher share of the middle and low skill unemployment rates variances (21.1% and 19.1%) while they account for 15.9% of the high skill unemployment rate variance.

[20] For instance, Darby et al. (1986) use a dataset from the manufacturing industry which is likely to contain unemployed mostly in middle skill occupations. This aspect could therefore affect their results.

	Unemployment rates		
	u^h	u^m	u^l
panel (a)			
From U vs To U			
β^{XU^h}	53.87	0.35	-0.21
β^{XU^m}	-0.06	39.36	-0.44
β^{XU^l}	0.18	0.01	33.83
β^{XU}	54.00	39.72	33.17
β^{U^hX}	46.91	0.63	-0.59
β^{U^mX}	-0.23	51.44	-0.46
β^{U^lX}	-0.26	1.18	61.35
β^{UX}	46.42	53.25	60.31
β^{XX}	-0.42	7.03	6.52
Tot	100.00	100.00	100.00
panel (b)			
Aggregate			
β^{EE}	-2.20	3.84	2.95
β^{EU}	28.13	28.79	23.88
β^{EI}	-0.46	-0.86	-0.13
$\beta^{U^iE^i}$	14.25	20.77	32.74
$\beta^{U^iE^j}$	16.25	11.43	8.51
β^{UE}	30.51	32.20	41.24
β^{UI}	15.92	21.05	19.06
β^{IE}	2.24	4.05	3.71
β^{IU}	25.87	10.93	9.29
Tot	100.00	100.00	100.00

Variance decomposition results for quarterly fluctuations of occupation-specific unemployment rates. The results in panel (a) aggregate contributions in terms of ins and outs of unemployment (e.g $\beta^{XU^h} = \beta^{E^hU^h} + \beta^{IU^h}$ and $\beta^{XU} = \beta^{XU^h} + \beta^{XU^m} + \beta^{XU^l}$). The second set of results (panel (b)) present contributions obtained by aggregating occupation groups (e.g $\beta^{EU} = \beta^{E^hU^h} + \beta^{E^mU^m} + \beta^{E^lU^l}$). The f^{UE} contribution is further disaggregated according to whether the transition is to the same occupation i, $f^{U^iE^i}$ or to a different occupation group j, $f^{U^iE^j}$.

Table 4: Occupation Specific Unemployment rates

4.2 Aggregate Unemployment Rate

Before discussing the results, it is worth mentioning that the contributions of aggregate hazard rates (panel (b) and 4th column in Table 5) are very similar to those reported by Elsby et al. (2015) in their Table 3 (fourth line), despite the differences in series of stocks and flow rates.[21] Table 5 indicates that variations of hazard rates from employment to unemployment (f^{EU}) accounts for 24.9% of the variance of aggregate unemployment rate fluctuations. For f^{UE}, f^{EI}, f^{UI}, f^{IE} and f^{IU}, the contributions are respectively, equal to 40.8%, -0.8%, 21%, 3.7% and 10.5%. Using data unadjusted for classification errors over the 1978-2012 time period, Elsby et al. (2015) report contributions of 22.3%, 35.1%, -

[21]For instance, I exclude *New Unemployed Entrants* and adjust series of flows between unemployment and inactivity for the 1994 redesign of the CPS (see Section 2.1).

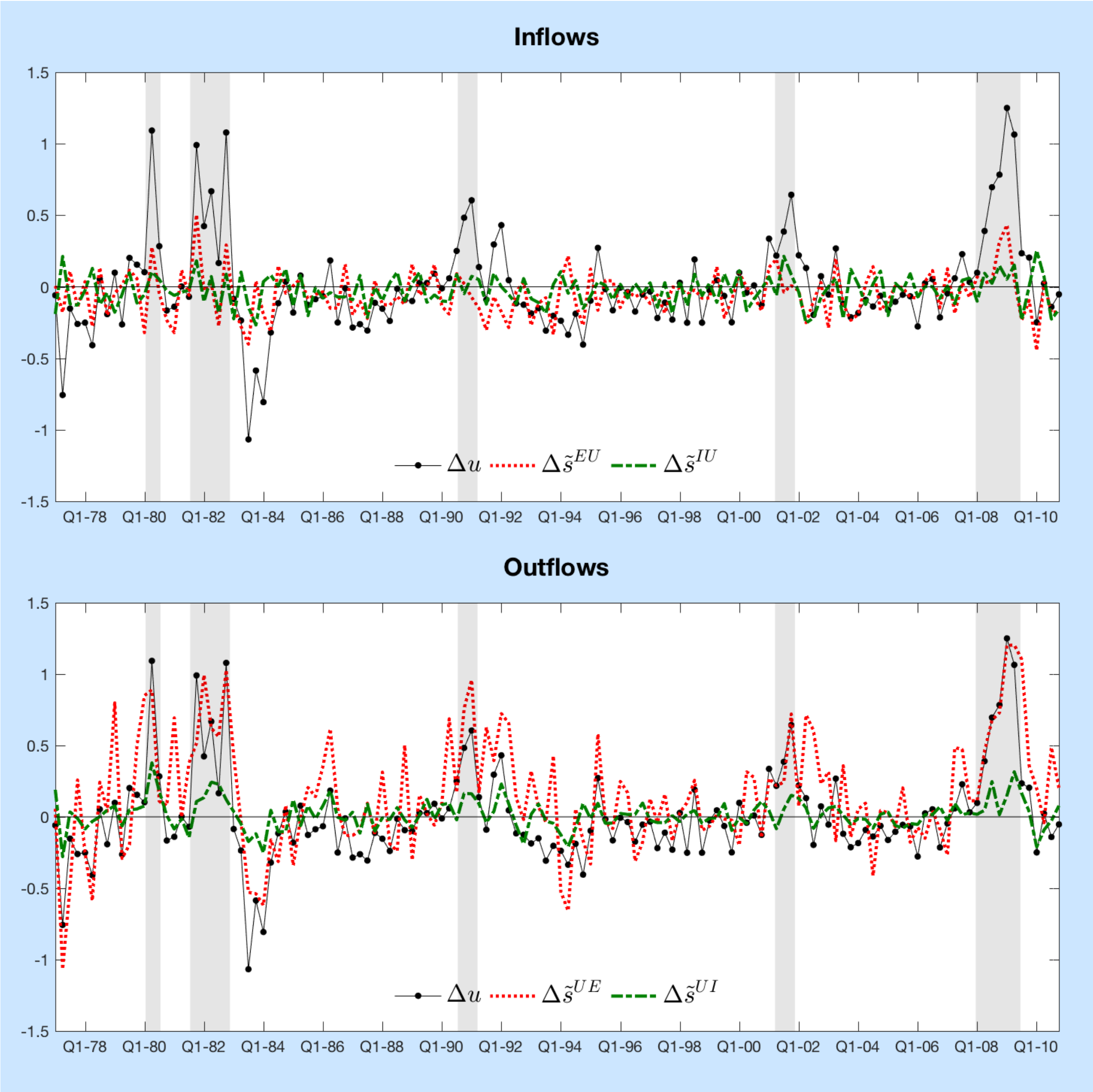
0.7%, 22.3%, 1.5% and 13.2%. Therefore, they find slightly higher contributions for flows between unemployment and inactivity (21% and 10.5% vs 22.3% and 13.2%) and lower ones for flows between employment and unemployment (24.9% and 40.8% vs 22.3% and 35.1%).[22]

	Unemployment rate			
	Hazard Rate	Composition		Total
	Δf	Middle skill	Low skill	
panel (a)				
From U vs To U				
β^{XU^h}	6.19	-	-	6.19
β^{XU^m}	13.97	-	-	13.97
β^{XU^l}	15.74	-	-	15.74
β^{XU}	35.90	-0.13	-0.39	35.38
β^{U^hX}	8.71	-	-	8.71
β^{U^mX}	20.54	-	-	20.54
β^{U^lX}	32.27	-	-	32.27
β^{UX}	61.53	0.32	-0.04	61.81
β^{XX}	2.84	-0.01	-0.01	2.82
Tot	100.26	0.18	-0.44	100.00
panel (b)				
Aggregate				
β^{EU}	25.41	-0.13	-0.39	24.89
β^{EI}	-0.81	-0.01	-0.01	-0.83
$\beta^{U^iE^i}$	28.09	-	-	28.09
$\beta^{U^iE^j}$	12.53	-	-	12.53
β^{UE}	40.62	0.22	-0.03	40.81
β^{UI}	20.90	0.10	-0.00	21.00
β^{IE}	3.65	-	-	3.65
β^{IU}	10.48	-	-	10.48
Tot	100.26	0.18	-0.44	100.00

Variance decomposition results for quarterly fluctuations of the aggregate unemployment rate. The results in panel (a) aggregate contributions in terms of ins and outs of unemployment (e.g $\beta^{XU^h} = \beta^{E^hU^h} + \beta^{IU^h}$ and $\beta^{XU} = \beta^{XU^h} + \beta^{XU^m} + \beta^{XU^l}$). The second set of results (panel (b)) present contributions obtained by aggregating occupation groups (e.g $\beta^{EU} = \beta^{E^hU^h} + \beta^{E^mU^m} + \beta^{E^lU^l}$). The f^{UE} contribution is further disaggregated according to whether the transition is to the same occupation i, $f^{U^iE^i}$ or to a different occupation group j, $f^{U^iE^j}$. The first column displays results from fluctuations of occupation-specific hazard rates (hazard rate effect). The second and third columns give results for compositional effects. Note that variations of employment occupational shares, $\Delta E_t^m/E_t$ and $\Delta E_t^l/E_t$, affect aggregate hazard rates from employment (f^{EU} and f^{EI}) while $\Delta U_t^m/U_t$ and $\Delta U_t^l/U_t$ affect aggregate hazard rates from unemployment (f^{UE} and f^{UI}). The last column sums contributions of hazard rates and compositional effects. See Section 3.2 for more details.

Table 5: Aggregate Unemployment rate

[22]A potential reason for these differences could be the exclusion of *New Unemployed entrants* which have higher transition rates between unemployment and inactivity.



Hazard rates contributions in percentage points, to quarterly unemployment rate fluctuations in level. The top graph displays contributions from hazard rates into unemployment, $\Delta\tilde{s}^{EU}$ and $\Delta\tilde{s}^{IU}$. The bottom graph shows contributions from hazard rates out of unemployment, $\Delta\tilde{s}^{UE}$ and $\Delta\tilde{s}^{UI}$. These 4 contributions sum occupation-specific hazard rate contributions (e.g. $\Delta\tilde{s}^{EU} = \Delta\tilde{s}^{E^hU^h} + \Delta\tilde{s}^{E^mU^m} + \Delta\tilde{s}^{E^lU^l}$). Contributions from the remaining hazard rates (f^{EI} and f^{IE}) and from composition effects are small and not displayed in this figure. Unemployment rate fluctuations, Δu_t are displayed in black and shaded areas correspond to recession periods as defined by the NBER.

Figure 3: Ins and Outs Contributions to Quarterly Fluctuations of the Unemployment Rate

A few aspects are worth noticing from Table 5. Firstly, Panel (a) shows that aggregate unemployment fluctuations are mostly explained by outflows from unemployment which account for 61.8% of the variance. Inflows contribute for 35.4% which is, nevertheless, a significant contribution. Therefore, these results suggest that both ins and outs matter to understand unemployment rate fluctuations (Elsby et al. (2009)). Secondly, Table 5 indicates that the occupational composition of (un)-employment, which affect the aggregate hazard rates f^{EU}, f^{EI}, f^{UE} and f^{UI} (see Section 3.2), have almost no impact on the variance of aggregate unemployment fluctuations. The fact that the focus of this paper is on short term (quarterly) fluctuations could explain this result and these compositional changes could be larger and play a more important role at lower frequency (e.g. 5-10 years).

Table 5 also displays results for contributions of ins and outs of occupation-specific unemployment (e.g. from and to high skill unemployment). These results show that transitions from and to high skill unemployment contribute for 14.9% (6.2%+8.7%) of the aggregate unemployment rate variance. On the other hand, ins and outs of middle and low skill unemployment contribute approximately for 34.5% and 48.0% respectively. These contributions are similar to the occupational composition of unemployment. On average over the 1976-2010 period, high skill unemployment represent 16.1% of aggregate unemployment, the average middle skill unemployment share is 34.1% and the low skill one is 49.9%. The results in Table 5 also indicate that transition rates into middle and low skill unemployment have similar contributions (14.0% and 15.7%) and the difference between the 2 occupation groups originates solely from outflows. The outs of low skill unemployment contribute for 32.3% of the aggregate unemployment rate variance while outflows from middle skill unemployment explain 20.5%.

Finally, Figure 3 displays contributions from hazard rates into ($\Delta\tilde{s}^{EU}$ and $\Delta\tilde{s}^{IU}$) and out ($\Delta\tilde{s}^{UE}$ and $\Delta\tilde{s}^{UI}$) of unemployment. This figure shows that hazard rates out of unemployment to employment have the largest contributions to unemployment rate fluctuations in level, particularly during recessions. Despite explaining a bit more than 1/3 of the aggregate unemployment variance, hazard rates into unemployment appear to have relatively small contributions in level. However, the contribution from f_t^{EU} spikes during the 1980-82 and 2007-09 recessions. This is consistent with an observation made by Elsby et al. (2010) about the fact that this hazard rate significantly increased during these 2 severe recessions while its variations were small during the other 2 recessions. For hazard rates between unemployment and inactivity, it is interesting to note that the signs of contributions matches the cyclical behavior of these transition rates during recessions. The hazard rate f^{UI} is procyclical and decreases which contributes positively to unemployment fluctuations. On the other hand, f^{IU} contributions are smaller but this hazard rate is countercyclical and increases during recessions which also contributes positively to unemployment fluctuations.

4.3 Labor Force Participation Rate

Panel (a) in Table 6 aggregates contribution in terms of ins and outs of the labor force. From these results, we see that outflows account for 34.4% of the variance of quarterly labor force partcipation fluctuations. As explained in Section 3.2, this contribution can be decomposed into hazard rates effects and compositional effects.

The compositional effect captures two different mechanisms. Firstly, changes in the occupational composition of (un)-employment, $\Delta E_t^i/E_t$ and $\Delta U_t^i/U_t$, affect aggregate exit rates from (un)-employment, f_t^{EI} and f_t^{UI}. As can be seen from Table 6, occupational composition effect (3rd and 4th columns of Table 6) have small contributions to quarterly fluctuations of labor force participation similar to what is reported for unemployment in the previous section. The second composition effect works through variations of the unemployment rate, Δu_t (2nd column of Table 6), which affect outflows to out of the labor force, $f_t^{\mathrm{lf}I}$. This composition effect contributes for 40.09% of the labor force participation variance which is more than the total outflow contribution.

The combined effects of hazard rates, f_t^{EI} and f_t^{UI} are small (-3.52%) but panel (b) shows that this contribution hides a negative contribution from f_t^{UI}. This seems to indicate that the procyclicality of outflows from unemployment to inactivity, which decrease during recessions, are important to dampen the variations of labor force participation.[23]

[23]Note that, from equation (10), a negative contribution implies that the covariance between the fluctuations of the stock and the contributions from a given hazard rate is negative. In other words, when fluctuations of labor force participation are positive (negative), the contributions from the hazard rate f_t^{UI} tend to be negative (positive).

	Labor Force Participation				
	Hazard Rate	Composition			Total
	Δf	Δu	Middle skill	Low skill	
panel (a)					
From lf vs To lf					
$\beta^{\text{lf}^h I}$	0.23	-	-	-	0.23
$\beta^{\text{lf}^m I}$	-4.72	-	-	-	-4.72
$\beta^{\text{lf}^l I}$	0.97	-	-	-	0.97
$\beta^{\text{lf}I}$	-3.52	40.09	-1.11	-1.09	34.37
$\beta^{I\text{lf}^h}$	11.20	-	-	-	11.20
$\beta^{I\text{lf}^m}$	25.02	-	-	-	25.02
$\beta^{I\text{lf}^l}$	29.40	-	-	-	29.40
$\beta^{I\text{lf}}$	65.63	-	-	-	65.63
Tot	62.11	40.09	-1.11	-1.09	100.00
panel (b)					
Aggregate					
β^{EI}	14.24	-	-0.84	-0.77	12.63
β^{UI}	-17.76	-	-0.27	-0.33	-18.36
β^{IE}	45.87	-	-	-	45.87
β^{IU}	19.76	-	-	-	19.76
Tot	62.11	-	-1.11	-1.09	59.91

Variance decomposition results for quarterly fluctuations of the labor force participation rate. The results in panel (a) aggregate contributions in terms of ins and outs of the labor force (e.g. $\beta^{I\text{lf}^h} = \beta^{IE^h} + \beta^{IU^h}$ and $\beta^{I\text{lf}} = \beta^{I\text{lf}^h} + \beta^{I\text{lf}^m} + \beta^{I\text{lf}^l}$). The second set of results (panel (b)) presents contributions obtained by aggregating occupation groups (e.g. $\beta^{EI} = \beta^{E^h I} + \beta^{E^m I} + \beta^{E^l I}$). The first column displays contributions of occupation-specific hazard rate (or hazard rate effects). The second, third and fourth columns give results for compositional effects. Note that Δu only affect the aggregate outflows from the labor force, $f^{\text{lf}I}$ and its contribution $\beta^{\text{lf}I}$. Variations in occupational composition of employment, $\Delta E_t^m/E_t$ and $\Delta E_t^l/E_t$, affect the aggregate hazard rates from employment, f^{EI} while $\Delta U_t^m/U_t$ and $\Delta U_t^l/U_t$ affect the aggregate hazard rates from unemployment, f^{UI}. The last column sums hazard rates and composition effects. The total contribution of panel (b) does not sum to 100 given that Δu does not affect aggregate contributions β^{EU}, β^{EI}, ... See Section 3.2 for more details.

Table 6: Labor Force Participation

The top graph in Figure 4 allows to gain a better idea of the various forces affecting the outflow contributions. This figure clearly shows that during recessions, the increase in the unemployment rate contributes negatively to labor force participation fluctuations through its positive effect on the outflow rate $f^{\text{lf}I}$. On the other hand, the decrease in f^{UI} has a substantial positive contributions which allows to dampen the negative effect from the increase in the unemployment rate. Note also that f^{EI}

is mildly procyclical and the decrease in this transition rate also contributes positively to labor force fluctuations during recessions.

The analysis of outflows confirms the results of Barnichon (2019) and Elsby et al. (2019) and highlights the role played by fluctuations of the unemployment rate.[24] During recessions, outflows from the labor force increase because of the increase in the unemployment rate. However, hazard rates from the labor force to inactivity, in particular from unemployment, play a key role in offsetting the negative effects of the unemployment rate and dampen labor force fluctuations. Therefore, the cyclical behavior of these two hazard rates, f^{EI} and f^{UI}, appears to be important to understand the mild procyclicality of labor force.

Turning to inflows, f^{IE} and f^{IU}, the results in Table 6 imply that the bulk of quarterly fluctuations of the labor force participation rate are explained by these 2 hazard rates. The ins account for 65.6% of the variance with around 70% of this contribution originating from inflows to employment (45.9% from panel (b)). The importance of transition rates into the labor force stands in contrast with the conclusion reached by Barnichon (2019). Using a 2 state decomposition and the framework of Fujita and Ramey (2009), he argues that hazard rates out of the labor force are the main drivers of labor force fluctuations. Restricting his sample to individuals aged 25-55, he claims that over the period 1976-2018, outflows account for 55% of the variance of the labor force participation rate (and even 84% over the 1990-2018 period). However, instead of focusing on quarterly fluctuations of hazard rates and labor force participation (as is the case in this work), he studies deviations of these quantities from their means. This leads to an analysis of different time series for labor force participation and hazard rates which can explain the opposite conclusions reached in this work.[25]

On the other hand, a recent paper by Cairo et al. (2019) studies the cyclicality of the labor force participation rate in search and matching models. They argue that the ability of the model to reproduce the mild procyclicality of labor force participation is closely related to whether the model matches the procyclicality of the transition rate from inactivity to employment.[26] The results in Table 6 highlight the role of f^{IE} which can be seen as supporting their emphasis on this particular transition rate.

In terms of occupations-specific hazard rates, Table 6 shows that inflows to middle and low skill labor force account for more than half of the variance (respectively for 25.0% and 29.4%) and for 80% of the inflow contribution (54.4%/65.6%). These 2 occupation groups represent 64.8% of the labor force on average (respectively 35.2%, 31.6% and 33.2% for high, middle and low skill occupations) which highlights the importance of inflows to these 2 occupations representing 2/3 of the labor force but 80% of the inflow contribution.

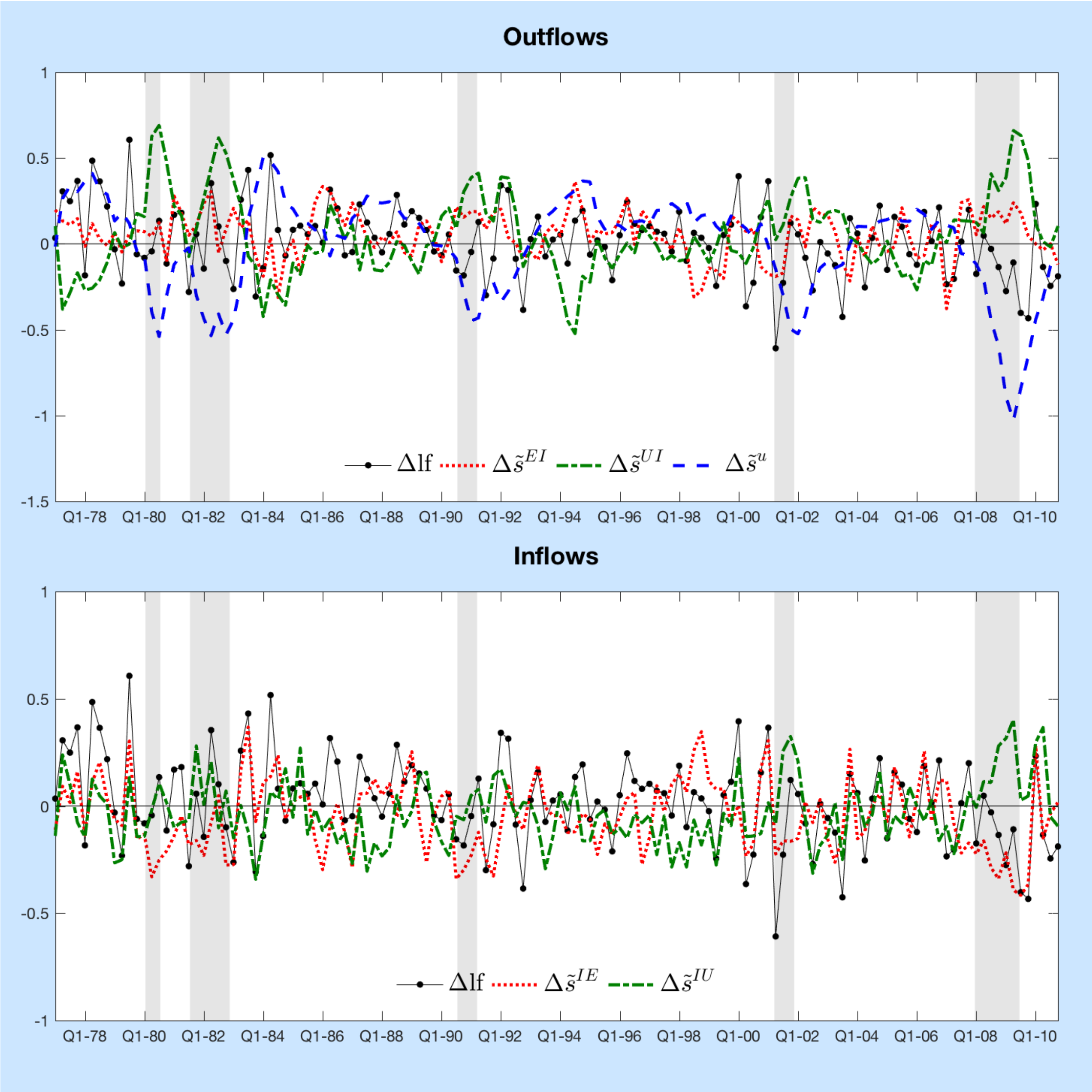
Finally, the graphical analysis of inflows in Figure 4 (bottom graph) shows that the inflow contributions (usually) result from hazard rate contributions of opposite signs. In particular, during recessions, the inflow to unemployment, f^{IU}, increases which contributes positively to labor force fluctuations. On the other hand, the decrease of f^{IE} puts a negative pressure on labor force participation. Similarly to outflows, contributions of inflows are therefore the results of offsetting forces which are also likely

[24] Note that Elsby et al. (2019) emphasize the role of hazard rates between employment and unemployment, f^{EU} and f^{UE} which do not explicitly appear in the hazard rate decomposition used in this work (see footnote 14). However, the effects of these hazard rates are implicitly contained into the fluctuations of the unemployment rate. Table 5 shows that these two hazard rates account for 65% of the variance of the aggregate unemployment rate. Since f^{EU} and f^{UE} explain most of the variance of Δu, we can expect that these 2 hazard rates account for an important share of the 40% explained by Δu_t.

[25] Note that by removing the mean, the labor force series studied by Barnichon (2019) still features the trends present in the original series (increase until 2000 and decrease after). This raises questions about decomposing the variance of a non stationary series. Furthermore, the decomposition proposed by Fujita and Ramey (2009) (which is based on the steady state decomposition of the stock of interest) can also be used to study quarterly fluctuations of a stock or its cyclical component extracted using the hp-filter (deviations from trend). I have applied this decomposition using both quantities and found that ins account for 75% of the variance, more in line with the results reported in Table 6.

[26] Cairo et al. (2019) argue that in recessions, transition rates between unemployment and inactivity tend to put upward pressure on participation through a decrease of f_t^{UI} and an increase of f_t^{IU}. The decrease of f_t^{IE} is therefore important to counteract these positive pressures.

contributing to the the mild procyclicality of labor force participation.



Hazard rates contributions in percentage points, to quarterly fluctuations of labor force participation in level. The top graph displays contributions from outflows decomposed into the contributions of hazard rates out of the labor force, $\Delta\tilde{s}_t^{EI} = \Delta\tilde{s}_t^{E^hI} + \Delta\tilde{s}_t^{E^mI} + \Delta\tilde{s}_t^{E^lI}$ and $\Delta\tilde{s}_t^{UI} = \Delta\tilde{s}_t^{U^hI} + \Delta\tilde{s}_t^{U^mI} + \Delta\tilde{s}_t^{U^lI}$ and the composition effect from unemployment variations, $\Delta\tilde{s}^u$. Occupational composition effects are small and not displayed in this figure. The bottom graph shows inflows contributions, $\Delta\tilde{s}_t^{IE} = \Delta\tilde{s}_t^{IE^h} + \Delta\tilde{s}_t^{IE^m} + \Delta\tilde{s}_t^{IE^l}$ and $\Delta\tilde{s}_t^{IU} = \Delta\tilde{s}_t^{IU^h} + \Delta\tilde{s}_t^{IU^m} + \Delta\tilde{s}_t^{IU^l}$. Labor force participation fluctuations, Δlf are displayed in black and shaded areas correspond to recession periods as defined by the NBER.

Figure 4: Ins and Outs Contributions to Quarterly Fluctuations of Labor Force Participation

5 Conclusion

Using CPS data over the 1976-2010 period and the variance decomposition proposed by Elsby et al. (2015), this paper studies the role of aggregate and disaggregated hazard rates by occupations, in driving short term fluctuations of labor market stocks.

Accounting for the occupational dimension reveals some interesting differences between the dynamics of disaggregated unemployment rates. Fluctuations of the high skill (or cognitive occupations) unemployment rate are mostly explained by hazard rates into unemployment, whereas the outs drive variations of the low skill (manual occupations) unemployment rate. For the high skill unemployment rate, the higher contributions of inflows originates from inflows from inactivity while outflows to employment are particularly important for fluctuations of the low skill unemployment rate.

This paper also focuses on the fluctuations of the aggregate unemployment rate and labor force participation. I show how the framework used to study variations of occupation-specific stocks, can be applied for the analysis of these aggregate stocks fluctuations. This allows to study the effects of occupation-specific hazard rates but also the role of variations in the occupational composition of (un)-employment.

The variance decomposition results show that these compositional effects do not matter for short term fluctuations of the aggregate unemployment rate. I find that hazard rates out of unemployment to employment and to inactivity explain around 60% of the variance in aggregate unemployment fluctuations whereas hazard rates to unemployment from employment and from inactivity account for the remaining share. This suggests that both types of transitions are required to understand the dynamics of the unemployment rate (Elsby et al. (2009)). Furthermore, hazard rates into and out of middle and low skill unemployment account for more than 80% of the variance in fluctuations of the unemployment rate. The graphical analysis of these contributions also reveals the significant role of outflows to employment particularly during recessions.

The analysis of labor force participation allows to better understand the mechanisms behind the fluctuations of this stock. The results of the variance decomposition show that flows out of the labor force explain around 35% of its variance and unemployment rate variations account for the entirety of this contribution. This highlight the key role played by unemployment on labor force fluctuations: when unemployment increases (during a recession for instance), the exit rate from the labor force increases as well which exerts negative pressure on labor force participation. However, this effect is partly compensated by the hazard rate from unemployment to inactivity which decreases and limits the increase in outflows. On the other hand, I find that inflows to the labor force account for 65% of its variance with hazard rates to employment contributing for 45% and hazard rates to unemployment for 20%.

Taken together, these results imply that during recessions, the increase in the unemployment rate and the decrease in hazard rates from inactivity to employment, f^{IE}, have a negative impact on labor force fluctuations through an increase in outflows and a decrease in inflows. However, hazard rates from the labor force to inactivity, f^{EI} and f^{UI}, decrease which limits the increase in outflows. Furthermore, the hazard rate from inactivity to unemployment, f^{IU}, increases which has a positive effect on inflows. The mild procyclicality of labor force participation is therefore the result of various hazard rates and composition effects which offset each other and dampen the fluctuations in this stock.

Despite the substantial adjustments performed in Ounnas (2019), the data used in this paper could still suffer from misclassification errors between unemployment and inactivity as well as spurious occupational mobility. Implementing some adjustments proposed in the literature could therefore help to make the results obtained in this paper more robusts. Moreover, this paper focused on the occupational dimension of labor market fluctuations but this framework could be used to analyze effects of other common dimension of heterogeneity such as age or gender. Finally, the results obtained in this paper are more of a descriptive nature. Further research would be needed to understand why inflows to unemployment have higher contributions to fluctuations of the high skill unemployment rate or why outflows from unemployment matter more for low skill unemployment rate fluctuations. Understanding the cyclical behavior of the employment to inactivity and inactivity to unemployment hazard rates would also be important given the role that these transition rates play in dampening labor force fluctuations.

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A Appendix

A.1 Data

A.1.1 Cyclical properties of stocks using different Filers

Hamilton (2018) Filter

Hamilton (2018) proposes to extract the cyclical component as the residuals from the following regression:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3}$$

For quarterly data, Hamilton (2018) recommends setting $h = 8$ which is the value used to compute the results displayed in Tables 7 and 10.

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Employment				
E	0.0210	0.650	0.877	0.902
E^h	0.0206	0.638	0.709	0.871
E^m	0.0303	0.939	0.646	0.891
E^l	0.0202	0.624	0.491	0.773
Unemployment				
u	0.2120	6.559	-0.851	0.899
u^h	0.2095	6.482	-0.702	0.882
u^m	0.2084	6.448	-0.805	0.910
u^l	0.2057	6.366	-0.852	0.887
Labor force				
lf	0.0075	0.231	0.582	0.846

The cyclical component x_t is extracted using the Hamilton Filter with $h = 8$. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 7: Cyclical Properties for quarterly average of stocks over the period 1976-2010 (2)

HP Filter with $\lambda = 10^5$

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Employment				
E	0.0160	0.652	0.880	0.951
E^h	0.0161	0.657	0.714	0.886
E^m	0.0205	0.834	0.654	0.889
E^l	0.0211	0.859	0.837	0.862
Unemployment				
u	0.1791	7.290	-0.894	0.960
u^h	0.2023	8.236	-0.814	0.943
u^m	0.1765	7.183	-0.878	0.945
u^l	0.1737	7.070	-0.912	0.956
Labor force				
lf	0.0055	0.224	0.575	0.838

The cyclical component x_t is extracted as 100 times the log deviation from the HP-filter trend with smoothing parameter $\lambda = 10^5$. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 8: Cyclical Properties for quarterly average of stocks over the period 1976-2010 (3)

Cyclical Component for series in Level using the HP Filter with $\lambda = 1600$

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Employment				
E	0.6105	0.004	0.839	0.901
E^h	0.2152	0.001	0.506	0.728
E^m	0.2769	0.002	0.772	0.799
E^l	0.2672	0.002	0.709	0.684
Unemployment				
u	0.7129	0.005	-0.869	0.911
u^h	0.3734	0.003	-0.867	0.892
u^m	0.8084	0.005	-0.869	0.888
u^l	0.9994	0.007	-0.849	0.898
Labor force				
lf	0.2339	0.002	0.488	0.655

The cyclical component x_t is extracted for series in level and using the HP-filter with smoothing parameter $\lambda = 1600$. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 9: Cyclical Properties for quarterly average of stocks over the period 1976-2010 (4)

A.1.2 Cyclical properties of flow rates using different Filers

Hamilton (2018) Filter

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$		σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Emp.					**Unemp.**				
Aggregate									
p^{EU}	0.122	3.779	-0.836	0.851	p^{UE}	0.134	4.132	0.707	0.859
p^{EI}	0.049	1.525	0.437	0.707	p^{UI}	0.087	2.683	0.739	0.824
High Skill									
$p^{E^hE^m}$	0.173	5.361	-0.086	0.716	$p^{U^hE^h}$	0.179	5.547	0.592	0.764
$p^{E^hE^l}$	0.143	4.439	0.071	0.677	$p^{U^hE^m}$	0.227	7.031	0.491	0.642
$p^{E^hU^h}$	0.117	3.626	-0.399	0.661	$p^{U^hE^l}$	0.186	5.763	0.390	0.585
p^{E^hI}	0.070	2.163	0.065	0.388	p^{U^hI}	0.112	3.456	0.497	0.613
Middle Skill									
$p^{E^mE^h}$	0.141	4.368	-0.069	0.753	$p^{U^mE^h}$	0.242	7.496	0.629	0.645
$p^{E^mE^l}$	0.096	2.984	0.251	0.491	$p^{U^mE^m}$	0.191	5.914	0.593	0.818
$p^{E^mU^m}$	0.125	3.860	-0.723	0.740	$p^{U^mE^l}$	0.154	4.773	0.591	0.710
p^{E^mI}	0.067	2.067	0.385	0.641	p^{U^mI}	0.091	2.810	0.689	0.759
Low Skill									
$p^{E^lE^h}$	0.145	4.491	0.129	0.760	$p^{U^lE^h}$	0.215	6.638	0.468	0.512
$p^{E^lE^m}$	0.076	2.360	0.019	0.529	$p^{U^lE^m}$	0.219	6.776	0.716	0.813
$p^{E^lU^l}$	0.125	3.865	-0.816	0.824	$p^{U^lE^l}$	0.127	3.928	0.724	0.798
p^{E^lI}	0.051	1.570	0.416	0.518	p^{U^lI}	0.108	3.339	0.724	0.812
Inactivity									
Aggregate									
p^{IE}	0.069	2.122	0.547	0.714					
p^{IU}	0.124	3.828	-0.733	0.851					
Skill									
p^{IE^h}	0.088	2.726	0.504	0.466					
p^{IE^m}	0.100	3.093	0.609	0.678					
p^{IE^l}	0.084	2.587	0.684	0.663					
p^{IU^h}	0.166	5.142	-0.548	0.709					
p^{IU^m}	0.145	4.495	-0.731	0.787					
p^{IU^l}	0.126	3.907	-0.695	0.827					

The cyclical component x_t is extracted using the Hamilton Filter with $h = 8$. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 10: Cyclical Properties for quarterly average of flow rates over the period 1976-2010 (2)

HP Filter with $\lambda = 10^5$

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$		σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Emp.					**Unemp.**				
Aggregate									
p^{EU}	0.091	3.694	-0.798	0.782	p^{UE}	0.121	4.937	0.867	0.916
p^{EI}	0.041	1.680	0.495	0.569	p^{UI}	0.080	3.273	0.790	0.870
High Skill									
$p^{E^hE^m}$	0.143	5.800	-0.027	0.567	$p^{U^hE^h}$	0.152	6.189	0.626	0.712
$p^{E^hE^l}$	0.133	5.422	0.160	0.624	$p^{U^hE^m}$	0.186	7.551	0.638	0.505
$p^{E^hU^h}$	0.124	5.055	-0.667	0.688	$p^{U^hE^l}$	0.172	6.985	0.474	0.521
p^{E^hI}	0.065	2.640	0.158	0.210	p^{U^hI}	0.106	4.296	0.540	0.583
Middle Skill									
$p^{E^mE^h}$	0.113	4.585	-0.170	0.645	$p^{U^mE^h}$	0.189	7.712	0.610	0.475
$p^{E^mE^l}$	0.076	3.078	0.109	0.156	$p^{U^mE^m}$	0.150	6.103	0.787	0.832
$p^{E^mU^m}$	0.104	4.234	-0.593	0.601	$p^{U^mE^l}$	0.131	5.351	0.729	0.651
p^{E^mI}	0.059	2.410	0.549	0.534	p^{U^mI}	0.077	3.153	0.760	0.696
Low Skill									
$p^{E^lE^h}$	0.136	5.532	0.129	0.688	$p^{U^lE^h}$	0.189	7.713	0.516	0.359
$p^{E^lE^m}$	0.068	2.748	-0.078	0.360	$p^{U^lE^m}$	0.182	7.415	0.798	0.783
$p^{E^lU^l}$	0.093	3.801	-0.811	0.777	$p^{U^lE^l}$	0.112	4.541	0.851	0.827
p^{E^lI}	0.042	1.721	0.347	0.267	p^{U^lI}	0.092	3.729	0.742	0.810
Inactivity									
Aggregate									
p^{IE}	0.061	2.476	0.816	0.683					
p^{IU}	0.099	4.048	-0.833	0.841					
Skill									
p^{IE^h}	0.086	3.500	0.479	0.281					
p^{IE^m}	0.079	3.232	0.742	0.512					
p^{IE^l}	0.067	2.722	0.703	0.449					
p^{IU^h}	0.125	5.068	-0.621	0.518					
p^{IU^m}	0.110	4.473	-0.759	0.715					
p^{IU^l}	0.102	4.153	-0.812	0.791					

The cyclical component x_t is extracted as 100 times the log deviation from the HP-filter trend with smoothing parameter $\lambda = 10^5$.. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 11: Cyclical Properties for quarterly average of flow rates over the period 1976-2010 (3)

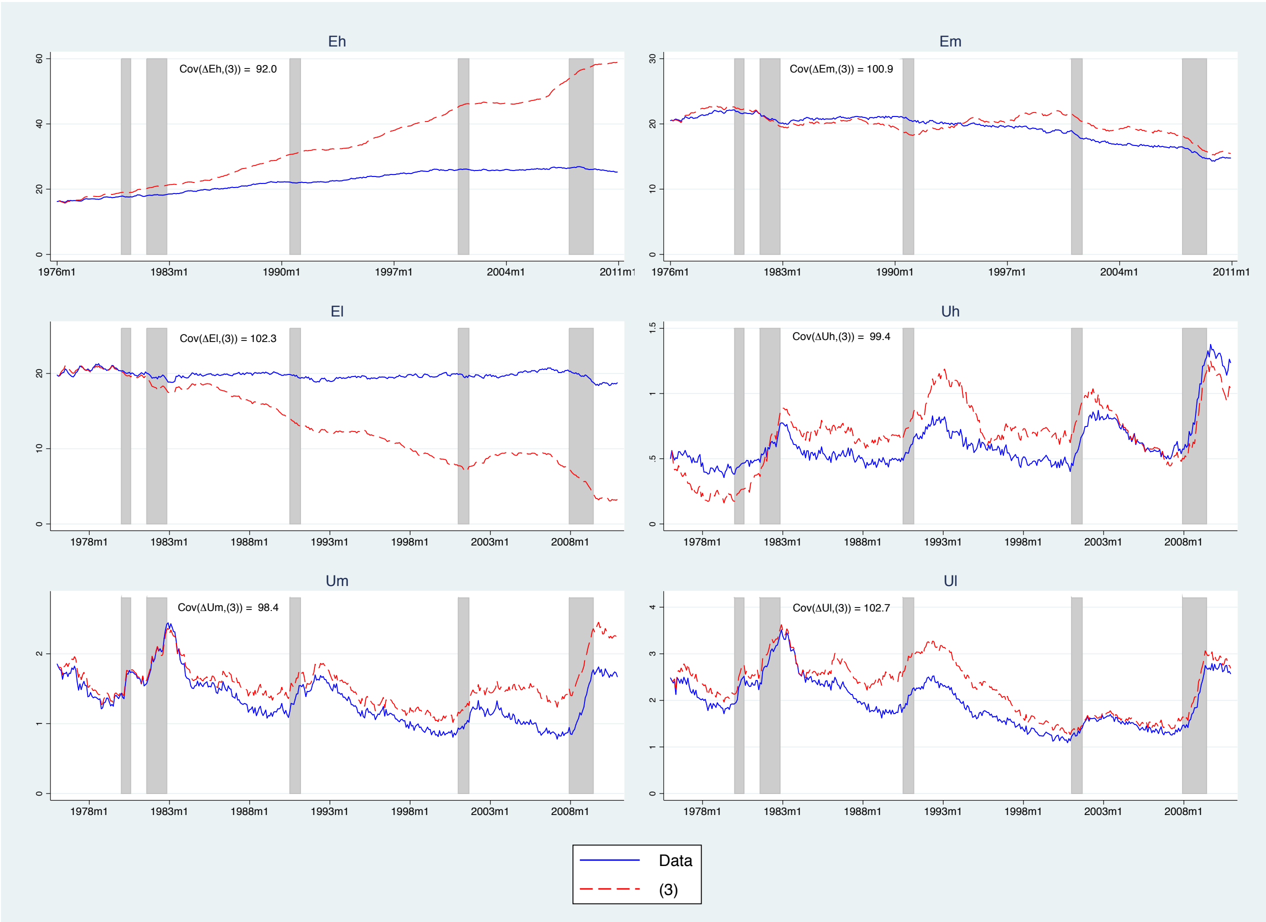
Cyclical Component for series in Level using the HP Filter with $\lambda = 1600$

	σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$		σ_{x_t}	$\frac{\sigma_{x_t}}{\sigma_{y_t}}$	ρ_{x_t,y_t}	$\rho_{x_t,x_{t-1}}$
Emp.					**Unemp.**				
Aggregate									
p^{EU}	0.109	0.001	-0.770	0.624	p^{UE}	2.052	0.014	0.824	0.810
p^{EI}	0.093	0.001	0.329	0.246	p^{UI}	1.155	0.008	0.752	0.739
High Skill									
$p^{E^hE^m}$	0.111	0.001	0.219	0.389	$p^{U^hE^h}$	1.721	0.012	0.550	0.459
$p^{E^hE^l}$	0.057	0.000	0.268	0.255	$p^{U^hE^m}$	1.014	0.007	0.558	0.277
$p^{E^hU^h}$	0.060	0.000	-0.675	0.558	$p^{U^hE^l}$	0.696	0.005	0.370	0.307
p^{E^hI}	0.094	0.001	0.043	-0.054	p^{U^hI}	1.455	0.010	0.587	0.348
Middle Skill									
$p^{E^mE^h}$	0.094	0.001	0.093	0.456	$p^{U^mE^h}$	0.353	0.002	0.459	0.303
$p^{E^mE^l}$	0.092	0.001	0.265	0.001	$p^{U^mE^m}$	1.508	0.010	0.695	0.672
$p^{E^mU^m}$	0.130	0.001	-0.632	0.462	$p^{U^mE^l}$	0.715	0.005	0.546	0.378
p^{E^mI}	0.145	0.001	0.356	0.231	p^{U^mI}	1.322	0.009	0.648	0.480
Low Skill									
$p^{E^lE^h}$	0.075	0.001	0.257	0.395	$p^{U^lE^h}$	0.243	0.002	0.268	0.159
$p^{E^lE^m}$	0.073	0.000	0.224	-0.027	$p^{U^lE^m}$	0.595	0.004	0.720	0.571
$p^{E^lU^l}$	0.165	0.001	-0.747	0.574	$p^{U^lE^l}$	1.582	0.011	0.743	0.591
p^{E^lI}	0.157	0.001	0.228	0.073	p^{U^lI}	1.331	0.009	0.622	0.627
Inactivity									
Aggregate									
p^{IE}	0.215	0.001	0.643	0.393					
p^{IU}	0.161	0.001	-0.722	0.627					
Skill									
p^{IE^h}	0.076	0.001	0.255	0.002					
p^{IE^m}	0.096	0.001	0.576	0.223					
p^{IE^l}	0.127	0.001	0.504	0.143					
p^{IU^h}	0.037	0.000	-0.555	0.352					
p^{IU^m}	0.073	0.000	-0.612	0.483					
p^{IU^l}	0.081	0.001	-0.633	0.518					

The cyclical component x_t is extracted for series in level using the HP-filter with smoothing parameter $\lambda = 1600$. The first column reports the standard deviation of x_t, the second column displays the standard deviation of x_t relative to the standard deviation of the cyclical component of GDP, y_t. The third shows the correlation between x_t and y_t and the last column computes the autocorrelation at lag 1 for x_t. The superscript h, m and l stand for high, middle and low skill.

Table 12: Cyclical Properties for quarterly average of flow rates over the period 1976-2010 (4)

A.2 Variance Decomposition



Comparison of stocks obtained using recursion (3) in red with their data counterparts in blue. Stocks are measured in percentages.

Figure 5: Stocks from Data and Recursion (3)

	u^h			u^m			u^l		
	Orig.	KF	KS	Orig.	KF	KS	Orig.	KF	KS
From E									
$\beta^{E^hE^m}$	-2.7	-2.6	-2.7	2.5	2.5	2.6	1.5	1.3	1.3
$\beta^{E^hE^l}$	-0.9	-0.8	-0.9	0.9	0.9	1.0	2.5	2.4	2.3
$\beta^{E^mE^h}$	0.2	0.3	0.2	0.2	0.2	0.3	0.0	-0.2	-0.2
$\beta^{E^mE^l}$	0.2	0.3	0.2	-0.3	-0.3	-0.2	0.8	0.6	0.6
$\beta^{E^lE^h}$	1.0	1.1	1.0	-0.3	-0.3	-0.2	-0.5	-0.6	-0.7
$\beta^{E^lE^m}$	0.0	0.1	0.0	0.4	0.4	0.4	-0.1	-0.3	-0.3
$\beta^{E^hU^h}$	27.8	27.9	27.8	0.3	0.3	0.4	0.3	0.1	0.1
$\beta^{E^mU^m}$	0.1	0.2	0.1	28.1	28.2	28.2	0.3	0.1	0.1
$\beta^{E^lU^l}$	0.2	0.3	0.2	0.1	0.1	0.1	24.0	23.7	23.7
β^{E^hI}	-1.9	-1.8	-1.9	1.1	1.1	1.2	1.3	1.1	1.1
β^{E^mI}	0.6	0.7	0.6	-2.2	-2.2	-2.2	0.3	0.1	0.1
β^{E^lI}	0.9	1.0	0.9	0.1	0.1	0.1	-1.1	-1.2	-1.3
from U									
$\beta^{U^hE^h}$	14.6	14.7	14.6	-0.5	-0.5	-0.4	-0.6	-0.7	-0.8
$\beta^{U^hE^m}$	8.8	8.8	8.7	1.0	1.0	1.1	0.0	-0.1	-0.2
$\beta^{U^hE^l}$	6.7	6.8	6.7	0.0	0.0	0.1	0.7	0.6	0.5
$\beta^{U^mE^h}$	0.6	0.7	0.6	1.1	1.1	1.1	-0.1	-0.3	-0.3
$\beta^{U^mE^m}$	-0.1	-0.0	-0.1	21.3	21.4	21.4	-0.5	-0.7	-0.7
$\beta^{U^mE^l}$	-0.1	-0.0	-0.1	6.9	6.9	7.0	1.4	1.3	1.2
$\beta^{U^lE^h}$	0.2	0.3	0.2	-0.1	-0.1	-0.0	0.8	0.6	0.6
$\beta^{U^lE^m}$	0.1	0.2	0.1	2.1	2.1	2.2	6.8	6.7	6.6
$\beta^{U^lE^l}$	-0.2	-0.1	-0.2	-0.3	-0.3	-0.3	34.4	34.2	34.2
β^{U^hI}	16.9	17.0	16.9	-0.2	-0.2	-0.1	0.0	-0.1	-0.2
β^{U^mI}	-0.6	-0.5	-0.6	21.8	21.8	21.9	-0.5	-0.7	-0.7
β^{U^lI}	-0.4	-0.3	-0.4	-0.8	-0.8	-0.7	20.1	19.9	19.9
From I									
β^{IE^h}	1.7	1.8	1.7	-0.1	-0.1	-0.1	0.3	0.1	0.1
β^{IE^m}	0.3	0.4	0.3	3.5	3.5	3.6	-0.1	-0.3	-0.3
β^{IE^l}	0.2	0.3	0.2	0.5	0.5	0.5	4.2	4.0	4.0
β^{IU^h}	26.1	26.2	26.1	-0.1	-0.1	-0.1	-0.1	-0.3	-0.3
β^{IU^m}	-0.2	-0.1	-0.2	11.1	11.1	11.1	-0.4	-0.5	-0.6
β^{IU^l}	-0.0	0.1	-0.0	-0.2	-0.2	-0.1	10.4	10.2	10.2
Tot	100.2	103.1	100.0	97.8	98.1	100.0	106.3	100.9	100.0

Table 13: Comparison of the Variance Decomposition Results for Occupational Unemployment Rates obtained using the Kalman Filter and Smoother

	u			lf		
	Orig.	KF	KS	Orig.	KF	KS
From E						
$\beta^{E^h U^h}$	3.5	3.6	3.6	-	-	-
$\beta^{E^m U^m}$	9.9	10.3	10.3	-	-	-
$\beta^{E^l U^l}$	11.1	11.5	11.5	-	-	-
$\beta^{EU} - comp\ E^m$	-0.2	-0.1	-0.1	-	-	-
$\beta^{EU} - comp\ E^l$	-0.4	-0.4	-0.4	-	-	-
$\beta^{E^h I}$	0.1	0.0	0.0	3.6	3.3	3.3
$\beta^{E^m I}$	-0.1	-0.5	-0.5	3.1	2.9	2.8
$\beta^{E^l I}$	-0.4	-0.4	-0.4	8.3	8.1	8.1
$\beta^{EI} - comp\ E^m$	-0.0	-0.0	-0.0	-0.6	-0.8	-0.8
$\beta^{EI} - comp\ E^l$	-0.0	-0.0	-0.0	-0.5	-0.7	-0.8
From U						
$\beta^{U^h E^h}$	3.0	3.1	3.1	-	-	-
$\beta^{U^h E^m}$	1.5	1.6	1.6	-	-	-
$\beta^{U^h E^l}$	1.3	1.4	1.4	-	-	-
$\beta^{U^m E^h}$	0.7	0.8	0.8	-	-	-
$\beta^{U^m E^m}$	7.4	7.7	7.7	-	-	-
$\beta^{U^m E^l}$	3.6	3.8	3.8	-	-	-
$\beta^{U^l E^h}$	0.5	0.5	0.5	-	-	-
$\beta^{U^l E^m}$	4.3	4.5	4.5	-	-	-
$\beta^{U^l E^l}$	16.7	17.3	17.3	-	-	-
$\beta^{UE} - comp\ U^m$	0.2	0.2	0.2	-	-	-
$\beta^{UE} - comp\ U^l$	-0.1	-0.1	-0.0	-	-	-
$\beta^{U^h I}$	2.7	2.6	2.6	-2.8	-3.1	-3.1
$\beta^{U^m I}$	8.8	8.3	8.3	-7.3	-7.5	-7.5
$\beta^{U^l I}$	10.6	10.0	10.0	-6.9	-7.1	-7.1
$\beta^{UI} - comp\ U^m$	0.1	0.1	0.1	-0.0	-0.2	-0.3
$\beta^{UI} - comp\ U^l$	-0.0	-0.0	-0.0	-0.1	-0.3	-0.3
From I						
β^{IE^h}	0.3	0.5	0.5	9.1	8.9	8.9
β^{IE^m}	0.9	1.2	1.2	19.4	19.1	19.1
β^{IE^l}	1.4	1.9	1.9	18.1	17.9	17.9
β^{IU^h}	2.7	2.6	2.6	2.6	2.3	2.3
β^{IU^m}	3.8	3.6	3.6	6.2	5.9	5.9
β^{IU^l}	4.4	4.2	4.2	11.8	11.6	11.5
From lf to I						
$\beta^{\text{lf}I} - comp\ u$	-	-	-	40.3	40.1	40.1
Tot	98.2	99.5	100.0	104.2	100.4	100.0

Table 14: Comparison of the Variance Decomposition Results for Aggregate Stocks obtained using the Kalman Filter and Smoother

A.3 Complementary Results for Section 3

A.3.1 Full sample: detailed results

	u^h	u^m	u^l	u	lf
$\beta^{E^hE^m}$	-2.67	2.60	1.26	-	-
$\beta^{E^hE^l}$	-0.91	0.98	2.32	-	-
$\beta^{E^mE^h}$	0.19	0.26	-0.20	-	-
$\beta^{E^mE^l}$	0.19	-0.22	0.57	-	-
$\beta^{E^lE^h}$	1.00	-0.23	-0.66	-	-
$\beta^{E^lE^m}$	0.01	0.44	-0.34	-	-
$\beta^{E^hU^h}$	27.78	0.41	0.09	3.58	-
$\beta^{E^mU^m}$	0.13	28.24	0.12	10.32	-
$\beta^{E^lU^l}$	0.21	0.15	23.67	11.51	-
$\beta^{EU} - comp\ E^m$	-	-	-	-0.13	-
$\beta^{EU} - comp\ E^l$	-	-	-	-0.39	-
β^{E^hI}	-1.91	1.16	1.09	0.02	3.32
β^{E^mI}	0.56	-2.16	0.05	-0.46	2.84
β^{E^lI}	0.90	0.13	-1.27	-0.37	8.09
$\beta^{EI} - comp\ E^m$	-	-	-	-0.01	-0.84
$\beta^{EI} - comp\ E^l$	-	-	-	-0.01	-0.77
$\beta^{U^hE^h}$	14.57	-0.42	-0.77	3.08	-
$\beta^{U^hE^m}$	8.74	1.08	-0.17	1.61	-
$\beta^{U^hE^l}$	6.73	0.07	0.51	1.41	-
$\beta^{U^mE^h}$	0.56	1.15	-0.29	0.78	-
$\beta^{U^mE^m}$	-0.12	21.44	-0.72	7.71	-
$\beta^{U^mE^l}$	-0.12	6.99	1.24	3.76	-
$\beta^{U^lE^h}$	0.19	-0.03	0.60	0.49	-
$\beta^{U^lE^m}$	0.14	2.17	6.61	4.47	-
$\beta^{U^lE^l}$	-0.20	-0.26	34.22	17.31	-
$\beta^{UE} - comp\ U^m$	-	-	-	0.22	-
$\beta^{UE} - comp\ U^l$	-	-	-	-0.03	-
β^{U^hI}	16.87	-0.10	-0.17	2.61	-3.09
β^{U^mI}	-0.55	21.85	-0.68	8.29	-7.55
β^{U^lI}	-0.40	-0.70	19.92	10.00	-7.12
$\beta^{UI} - comp\ U^m$	-	-	-	0.10	-0.27
$\beta^{UI} - comp\ U^l$	-	-	-	-0.00	-0.33
β^{IE^h}	1.71	-0.08	0.09	0.47	8.89
β^{IE^m}	0.33	3.58	-0.35	1.24	19.12
β^{IE^l}	0.20	0.54	3.96	1.94	17.87
β^{IU^h}	26.09	-0.06	-0.30	2.61	2.31
β^{IU^m}	-0.19	11.13	-0.56	3.65	5.91
β^{IU^l}	-0.03	-0.13	10.16	4.22	11.54
$\beta^{\mathrm{lf}I} - comp\ u$	-	-	-	-	40.09
Tot	100.00	100.00	100.00	100.00	100.00

Table 15: Detailed Results of the Variance Decomposition

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