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Abstract

There is a growing literature studying unemployment dynamics by means of worker flow data between labor market states. This paper contributes to this literature stream by analyzing the dynamics of the Austrian unemployment rate applying novel worker flow data for 2005-2016. Our main results can be summarized along two dimensions: First, we show that worker flows between unemployment and inactivity are major determinants of unemployment fluctuations in Austria. Second, we show for the working-age population that the contribution of male worker flows to the overall variation of the unemployment rate is higher, but that this relation turns when it comes to the youth cohort. The gender differences are probably related to the early occupational and educational segregation of young men and women in Austria. The paper concludes by stressing a strong need for further empirical and theoretical research which aims to link structural differences in an economy with different responses to the business cycle.

JEL classification: C81; J21; J63;
Keywords: Worker flows; Unemployment dynamics; Gender; Unemployment gap; Austrian labour market; Youth unemployment

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1 Introduction

There is a growing literature studying unemployment dynamics by means of worker flow data[1]. Compared to stock-based analysis only, worker flows between employment, unemployment and inactivity (i.e. non-participation) much better reveal specific sources of business cycle variation of these three states. The present paper contributes to this literature stream by analyzing the dynamics of the Austrian unemployment rate applying novel worker flow data for 2005-2016. Our results are derived employing variance decomposition techniques similar to Elsby et al. (2015) and Razzu and Singelton (2016) and can be summarized along two dimensions.

First, we show that worker flows between unemployment and inactivity are major determinants of unemployment fluctuations in Austria, meaning that the participation margin matters. Interestingly, the estimated fraction is much higher compared to recent results for the UK and the US. Second, our results point to the importance of the gender dimension in explaining unemployment fluctuations. Specifically, we show that the contribution of male worker flows to the overall variation of the unemployment rate is higher. However, this relation turns when it comes to the youth cohort, a segment that has not been studied so far.

In order to embed our results into the literature and to highlight our contribution we start from the observation that it has been only very recently recognised that worker flows between unemployment and inactivity are important determinants for unemployment fluctuations over the business cycle[2]. For the US between 1967-2012, Elsby et al. (2015) attribute around 26% of the unemployment variance to flows between unemployment and inactivity. This share corresponds to 39% in Razzu and Singelton (2016) who analyse the US in the period 1990-2015. Similarly, estimates for the UK range from 25% (Smith 2011) to 27% (Razzu and Singelton 2016). These stylized facts are important

[1] A selection of the most important contributions is Shimer (2012), Fujita and Ramey (2009), Elsby et al. (2009), Gomes (2012), Kudlyak and Schwartzman (2012), Barnichon and Figura (2012), Petrongolo and Pissarides (2008), Elsby et al. (2011), Hairault et al. (2015), Smith (2011), Elsby et al. (2015), and Razzu and Singelton (2016).

[2] Many studies on unemployment dynamics deal with the participation margin. However, either they concentrate on equilibrium (steady-state) unemployment only, neglecting a potential history dependence in the transmission of changes in worker flows to changes in unemployment (Shimer 2012; Fujita and Ramey 2009; Elsby et al. 2009; Gomes 2012; Kudlyak and Schwartzman 2012; Barnichon and Figura 2012), or estimate variance contributions only for combinations of worker flows (Petrongolo and Pissarides 2008; Elsby et al. 2011; Hairault et al. 2015; Smith 2011). Only Elsby et al. (2015) and Razzu and Singelton (2016) concentrate explicitly on the role of these worker flows and disentangle unemployment dynamics into contributions of single flows.

ingredients for researchers to develop reasonable theoretical mechanisms (i.e. search-and-matching models) in order to study the causation of the observed dynamics. However, so far research on the role of inactivity for unemployment dynamics has been concentrated on the US and UK only (Elsby et al. 2015; Razzu and Singelton 2016)[3].

But can these findings be generalized to other economies as well? In this paper we present respective results for Austria, hence extending the evidence across the borders of Anglo-Saxon labor markets. In general, the latter are characterized by a far less generous welfare state compared to countries like Austria or Germany (Esping-Andersen 1990; Esping-Andersen 1999; Castles and Obinger 2008). In contrast to Anglo-Saxon labor markets, individuals in Austria might have a much stronger incentive to transit between activity and inactivity more often, e.g. for retirement, parental leaves, child and health care, or education and training. Additionally, in the early 2000s, Austria had undertaken significant pension reforms to reduce early retirement and increase participation of the elderly, hence, potentially triggering sudden flows to early retirement (inactivity). Given these reasons, we might expect a more prominent role of worker flows between unemployment and inactivity in accounting for unemployment fluctuations. Indeed, as expected, we estimate that 45% of the Austrian unemployment variance can be attributed to unemployment-inactivity flows.

Yet, the second dimension of our results is most closely related to the work of Razzu and Singelton (2016) who analyse worker flows to explain the dynamics of the unemployment gap between men and women in the US and the UK. To our knowledge this is so far the only study that investigates gender differences in this particular context. Their results indicate that the stronger rise in male unemployment after 2008 can be majorly explained by a greater cyclicality of employment-unemployment flows. This finding is in line with the recent proposition that unemployment dynamics over the business cycle are typically dominated by males due to the significant occupational segregation (see Peiro et al. (2012), Wood (2014), and Albanesi and Sahin (2017) for US evidence).

As the existing results are again limited to Anglo-Saxon labor markets, we present contrasting evidence for the Austrian case. In this respect we aim to elaborate on the above proposition that again underlying structural gender differences (e.g. in occupational choices) cause different business cycle responses

[3] Note that Petrongolo and Pissarides (2008), Elsby et al. (2011), and Hairault et al. (2015) provide results for Spain, France or a selected group of OECD-countries as well. However, as mentioned in the previous footnote, these studies are not comparable to our analysis.

of men and women. However, our approach deviates from the one employed by Razzu and Singelton (2016). As their analysis concentrates on the unemployment gap and gender-specific unemployment rates, it hides the proposed differences in the relative importance of men's and women's contribution to the *overall* unemployment dynamics. For this reason, we extend the variance-decomposition method used in Razzu and Singelton (2016) and Elsby et al. (2015) to estimate not only the contribution of each single worker flow, but also a summary measure reflecting how much variation in the *overall* unemployment rate can be explained by worker flows of males and females. The latter results will serve as a starting-point for a theoretical discussion.

We show that fluctuations of the Austrian unemployment rate are mainly induced by male worker flows, which account for 59% of the overall variation. Hence, this finding is consistent with previous literature. Our estimate increases to more than two-thirds for the prime-age cohort (25-49 years). We further look more carefully on the youth cohort (aged 15-24 years), a segment which has not been studied so far, but has specifically been targeted by policy makers in recent years (e.g. Scarpetta et al. 2010; Bell and Blanchflower 2010). Surprisingly, in this cohort, women contribute more to the overall variability than men, accounting for 56% compared to 36%[4]. Moreover, we find evidence that women's unemployment experience is dominated by worker flows out of unemployment, while men's is characterized by inflows into unemployment. After a thorough discussion of several alternative explanations and pitfalls, we conclude that the educational segregation of the Austrian youth may be responsible for these surprising results.

As a remainder, section 2 introduces the novel dataset and presents a brief generalization of available variance decomposition methods and specifically introduces the method of Elsby et al. (2015) without extensive notation and complexity. In section 3 we aim to compare our first results to the scarce evidence of the literature. In the subsequent section 4 we introduce the small extension of the model framework to account for gender differences when studying worker flow contributions to overall unemployment variation. Section 5 evaluates the robustness of our findings. In section 6, we aim to discuss several theoretical considerations to explain our empirical findings. The last section concludes.

[4] Note that the overall explained variance amounts to 92%.

2 Empirical specification

2.1 Variance decomposition

This section sketches a general framework for the analysis of roles of the various worker flows for unemployment dynamics. The basic idea of this subsection is to sketch a straightforward method to break down total variability of the changes in the unemployment rate into contributions of each worker flow or transition rate[5].

Several papers have provided us with frameworks to decompose unemployment variability into its flow contributions. Most of them start with a simple state-space system which maps the previous labour market stocks $\mathbf{s_{t-1}}$ into next-period stocks $\mathbf{s_t}$. The link between time periods is established through a transition matrix $\mathbf{\Lambda_t}$, which is based on worker flow estimates.

$$\mathbf{s_t} = \mathbf{\Lambda_t s_{t-1}} \tag{1}$$

where bold letters indicate matrices containing several labour market stocks, such as $s_i \in \{E, U, I\}$. Based on this system, most papers arrive - after different algebraic avenues - at a very basic equation for the decomposition of unemployment variability:

$$\Delta u_t = \sum \Delta C_{t\,k}^k \tag{2}$$

$$Var[\Delta u_t] = \sum Cov[\Delta u_t,\ \Delta C_t^k]_k \tag{3}$$

The total variance of changes in the unemployment rate is additively decomposed into k-contributions. In general, ΔC_t^k are single algebraic expressions capturing the variability of either a specific worker flow or bundles of it, and we will specify the expressions ΔC_t^k depending on the decomposition method. For example, Elsby et al. 2009, Shimer 2012, and Gomes 2012 use the steady-state unemployment rate $\Delta \bar{u}_t$ as an approximation for Δu_t to simplify their analyses. In this case, the single contributions ΔC_t^k are counterfactual (steady-state) unemployment-changes, under the assumption that all but the k^{th}-worker flow

5 We use first-differences for detrending our series (rates, stocks, and flows) from recent trend movements. Fujita and Ramey (2009), Fujita (2011), and Shimer (2012) have shown the sensitivity of the results with respect to the method of detrending. While Shimer (2012) uses quarterly data and HP-filtering with a very high smoothing parameter (10^5), the others choose first-differences. Smith (2011), Elsby et al. (2013), and Elsby et al. (2015) decompose the difference in unemployment rather than the level for the same purposes. Hairault et al. (2015) has compared results from HP-filtered series with those from first-differenced series, and conclude that for their case, the filtering method does not matter.

remain at their means. Smith 2011 has relaxed the steady-state approximation but provides specific expressions only for ΔC_t^{EU} and ΔC_t^{UE}. As the latest advancement, Elsby et al. 2015 suppose a framework which allows to decompose $Var[\Delta u_t]$ into every single worker-flow-contribution. This is appealing if the aim is to study the role of the participation margin. For this reason, we quickly sketch this framework without introducing to much notation and complexity.

Assuming that (either) population $W_t = E_t + U_t + I_t$ stays constant between two consecutive quarters, we can normalize it to one and simplify the system stated in (1) to

$$\underbrace{\begin{bmatrix} E_t \\ U_t \end{bmatrix}}_{\mathbf{s_t}} = \underbrace{\begin{bmatrix} 1-\lambda_{EU}-\lambda_{EI}-\lambda_{IE} & \lambda_{UE}-\lambda_{IE} \\ \lambda_{EI}-\lambda_{IU} & 1-\lambda_{UE}-\lambda_{UI}-\lambda_{IU} \end{bmatrix}}_{\tilde{\mathbf{\Lambda}}_\mathbf{t}} \underbrace{\begin{bmatrix} E_{t-1} \\ U_{t-1} \end{bmatrix}}_{\mathbf{s_{t-1}}} + \underbrace{\begin{bmatrix} \lambda_{IE} \\ \lambda_{IU} \end{bmatrix}}_{\mathbf{q_t}} \tag{4}$$

with states normalized by W_t, and a steady state of $\bar{\mathbf{s}}_\mathbf{t} = \left(\mathbf{I} - \tilde{\mathbf{\Lambda}}_\mathbf{t}\right)^{-1} \mathbf{q_t}$.

Following Elsby et al. 2015, we can write (4) as a weighted average of changes in the current steady state and the complete history of previous changes:

$$\mathbf{\Delta s_t} = \left(\mathbf{I} - \tilde{\mathbf{\Lambda}}_\mathbf{t}\right) \mathbf{\Delta \bar{s}_t} + \left(\mathbf{I} - \tilde{\mathbf{\Lambda}}_\mathbf{t}\right) \tilde{\mathbf{\Lambda}}_\mathbf{t-1} \left(\mathbf{I} - \tilde{\mathbf{\Lambda}}_\mathbf{t-1}\right)^{\mathbf{-1}} \mathbf{\Delta s_{t-1}} \tag{5}$$

Equation (5) is intuitive: Current changes in labour market stocks are shaped by changes in their underlying long-run values to which the stocks would converge over time if the system remained unchanged. Additionally, todays changes also depend on past changes whose impact fads out as time elapses.

To evaluate the contribution of each $\Delta\lambda_{ijt}$ on $\mathbf{\Delta s_t}$, we have to take two more steps. First, $\Delta\lambda_{ijt}$ depends on the time interval chosen for the estimation of the transition rates, i.e. one quarter. To make our analysis independent of this particular time interval, we can write $\bar{\mathbf{s}}_\mathbf{t}$ as its continuous-time analogue: $\bar{\mathbf{s}}_\mathbf{t} = -\mathbf{F_t}^{-1}\mathbf{g_t}$ with $\mathbf{F_t}$ and $\mathbf{g_t}$ as the continuous-time equivalents of $\tilde{\mathbf{\Lambda}}_\mathbf{t}$ and $\mathbf{q_t}$, respectively. The second step involves the derivation of each contribution of Δf_{ijt} (the continuous time-equivalent to $\Delta\lambda_{ijt}$). Taking a first-order Taylor approximation of $\bar{\mathbf{s}}_\mathbf{t-1}$ around t, we get

$$\mathbf{\Delta \bar{s}_t} \approx \sum \frac{\partial \bar{\mathbf{s}}_\mathbf{t}}{\partial f_{ijt}} \Delta f_{ijt}{}_{\,i\neq j} \tag{6}$$

For the contributions of each Δf_{ijt} to the variance of ΔU_t, we have to formulate expressions for ΔC_t^k, where k is now one of the six possible transitions ij,$i \neq j$. Inserting (6) into (5), we can think of ΔC_t^{ij} as a counterfactual change in the unemployment rate whereby we assume variation of only one particular f_{ij}. As all ΔC_t^{ij} add up additively to ΔU_t as in (3), $\mathbf{\Delta s_t} \approx \sum \mathbf{\Delta C_t}_{i\neq j}^{ij}$, we can apply the variance decomposition of (3):

$$\mathbf{\Delta C_t^{ij}} = \left(\mathbf{I} - \mathbf{\tilde{\Lambda}_t}\right)\frac{\partial \mathbf{\bar{s}_t}}{\partial f_{ij}}\Delta f_{ij} + \left(\mathbf{I} - \mathbf{\tilde{\Lambda}_t}\right)\mathbf{\tilde{\Lambda}_{t-1}}\left(\mathbf{I} - \mathbf{\tilde{\Lambda}_{t-1}}\right)^{-1}\mathbf{\Delta C_{t-1}^{ij}} \tag{7}$$

Expression 7 can be rearranged from an auto-regressive form to an finite moving-average format. This is appealing, as we can account for the effect of the initial value ($t = 0$) on our decomposition result[6]. Starting at $t = 0$ and assuming that in that period the steady-states $\mathbf{\Delta\bar{s}_0}$ are equal to the observed stocks $\mathbf{\Delta s_0}$, we can iterate (7) forward.

$$\mathbf{\Delta s_t} = \mathbf{A_t\Delta\bar{s}_t} + \sum_{x=1}^{t-1}\left(\prod_{s=0}^{x-1}\mathbf{F_{t-s}}\right)\mathbf{A_{t-x}\Delta\bar{s}_{t-x}} + \left(\prod_{s=0}^{t-1}\mathbf{B_{t-s}}\right)\mathbf{\Delta s_0} \tag{8}$$

with $\mathbf{A_t} = \left(\mathbf{I} - \mathbf{\tilde{\Lambda}_t}\right)$, and $\mathbf{B_t} = \left(\mathbf{I} - \mathbf{\tilde{\Lambda}_t}\right)\mathbf{\tilde{\Lambda}_{t-1}}\left(\mathbf{I} - \mathbf{\tilde{\Lambda}_{t-1}}\right)^{-1}$, and $\mathbf{\Delta\bar{s}_t}$ from equation 6.

Finally, $\mathbf{\Delta s_t}$ is measured in terms of population and ΔU_t is therefore not the unemployment rate, which typically is the focus of policy. The above derivation can be applied to $\mathbf{\Delta s}$ in terms of population and transformed into equivalents in terms of labor-force population (e.g. $u_t = U_t/L_t = U_t/(E_t + U_t)$). More specifically, Elsby et al. 2015 suggest a simple approximation of the unemployment rate[7]:

$$\Delta u_t \approx (1 - u_{t-1})\frac{\Delta U_t}{L_{t-1}} - u_{t-1}\frac{\Delta E_t}{L_{t-1}}, \tag{9}$$

The employment rate $e_t = E_t/(E_t+U_t)$ and the labour-force participation (rate) $L_t = l_t = E_t + U_t$ could be approximated with expressions only dependent on ΔU_t and ΔE_t in a similar way. Both, ΔU_t and ΔE_t, are then the sum of the respective contributions as stated in equation (7).

2.2 Dataset

We use microdata of the Austrian Mikrozensus (Labor Force Survey, LFS) for the period 2004Q1-2016Q4 provided by Statistik Austria (2016). The Austrian LFS is a rotating panel and interviews a sample of people drawn from whole the population up to five quarters. In total, each cross-section (quarter) comprises approximately 45,000 individuals.

6 As our time-series are not that long, we expect some imprecision in our results.

7 Remember, $L_t = l_t$ as we normalized stock to working-age population. The approximation results from $\Delta u_t = \Delta U_t/l_{t-1} - \Delta L(U_t/l_t)$ and assuming the last term in brackets to be $(U_t/l_t) = (U_{t-1}/l_{t-1})$.

Due to the rotating panel, the dataset allows us to match these individuals across interviews and to construct a quarter-to-quarter matched dataset comprised of individuals with information on (at least) two consecutive labor market states. The procedure of Schoiswohl and Wüger (2016) is applied to the raw data to correct for significant panel attrition. With an attrition-corrected panel-dataset, we are able to estimate unbiased gross worker flows and (discrete-time) transition rates for the Austrian labour market. Data on worker flows and transition rates used throughout the paper is seasonally adjusted using an X12-ARIMA multiplicative correction approach. Quarterly gross worker flows N_{ijt} are calculated as the (weighted) number of people transiting between labour market states i and j with $i, j \in \{E, U, I\}$.[8] Transition rates represent a measure for the probability to leave a certain labour market state within a quarter and are calculated according to $\lambda_{ijt} = \frac{N_{ijt}}{P_{ijt-1}} = \frac{N_{ijt}}{\sum_j N_{ijt}}$

The transition rates λ_{ijt} are discrete in nature and may be biased due to the temporal aggregation (time-aggregation bias) to the quarterly time-interval. Shimer (2012) suggests to use a simply correction method to recreate *continuous-time* transition rates f_{ijt} from the discretely measured ones (λ_{ijt}). Let $\mathbf{\Lambda_t}$ be the discrete-time transition matrix with the collection of discretely measured transition rates λ_{ijt}. Then $\tilde{\mu}_\mathbf{t}$ is the diagonal matrix of log-eigenvalues from a eigendecomposition of $\mathbf{\Lambda_t}$. It can be used to infer the continuous-time equivalent using the expression $\mathbf{\Lambda_t}$ by $\mathbf{F_t} = \mathbf{V_t}\tilde{\mu}_\mathbf{t}\mathbf{V_t}^{-1}$.[9]

3 A comparison of the Austrian labour market with the previous literature

As shown by Peiro et al. (2012), Wood (2014), Razzu and Singelton (2016), and Albanesi and Sahin (2017), the business cycle hit men and women quite differently and the gender dimension is highly important in understanding labor market dynamics. To relate our results more directly to the evidence in the literature, we have recalculated the variance-decomposition for the whole

[8] Employment also includes the self-employed.

[9] If a time-period consists of Δ equal sub-periods, then the idea behind the adjustment method is to assume a constant transition matrix $x_{t,\Delta}$ within each sub-period Δ and shrink this time-interval against zero. Let $x_{t,\Delta}$ be the transition matrix for *each* sub-period, and x_t the matrix for the whole period. Then both correspond via the eigenvalues of x_t, μ_t: $x_{t,\Delta} = x_t^{\Delta} = a_t \mu_t^{\Delta} a_t^{-1}$. The first equality is due to the fact that the whole-period transitions are regained from sub-period transitions by multiplying them. This translates directly into the eigendecomposition. In this respect, Shimer 2012 provides the details on the maths and on the conditions when this relation and $\lim_{\Delta \to 0} \mu_t^{\Delta} = log(\mu_t)$ hold. We arrive at $x_{t,0} = a_t log(\mu_t) a_t^{-1}$, with $x_{t,0}$ continuous-time equivalent of the discretely measured x_t.

working-age population and for each gender separately. For the whole working-age population we can directly compare our results to those of Elsby et al. (2015) and Razzu and Singelton (2016) which are summarized in Table 1. So far, they are the only studies breaking down the variation of the unemployment rate to contributions of single worker flows, as we do here. Elsby et al. (2015) provide results for the US only, while Razzu and Singelton (2016) present results for the US and UK. Both focus on the working-age population only.

First, comparing the results for Austria with the figures of the US and the UK we see that job-separations (UE) are rather similar for all three countries (around 25%), but job-finding (UE) is much less important in Austria (29% to around 40% in the US and UK). In general, the Austrian labor market is characterized by an almost equal importance of unemployment inflows (EU/IU, 47%) and outflows (UE/UI, 54%), while the Anglo-Saxon economies show a stronger dominance of the outflow-components (e.g. 37%/61% for the US, and 33%/55% for the UK). Interestingly, UI- and IU-flows are more important in Austria. More specifically, 45% of the unemployment variance is attributed to these flows in Austria, compared to 27%-39% in the US or UK. These results are of specific interest in several respects: Firstly, the conventional wisdom in the literature suggests that the cyclicality of the employment-unemployment margin solely accounts for the fluctuations of the unemployment rate (see e.g. Mortensen and Pissarides 1994; Shimer 2012; Fujita and Ramey 2009). Our results, however, show the opposite. Therefore, it is important to treat the participation margin as a separate margin. Secondly, Austria is characterized by a much greater importance of the participation margin compared to evidence for the US and the UK. Significant public welfare institutions such as large public pension schemes, generous parental leaves or public support for vocational trainings may trigger our observations for three reasons: (i) In case of non-employment (due to child-care, retirement, etc.), significant public welfare systems typically replace potential losses of wealth in these cases. (ii) They may also render individual decisions cyclical, either by determining the moment of entry into a specific program, the moment of exit, or both. (iii) Large public welfare schemes are subject to significant policy reforms, such as the several substantial pension reforms in Austria. While (i) and (ii) may be reasons for observing high shares for either UI, IU or both, (iii) may trigger major secular trends (e.g. in participation of the elderly) and thereby also cyclical fluctuations in transitions from/to inactivity.

As far as gender differences are concerned, Razzu and Singelton (2016) are so far the only study providing respective results in such a level of detail as we do in our paper. The gender dimension is tackled by looking at the unemployment rate of male and female workers separately and we repeat their analysis with Austrian data. In general, the results for males are similar for all three countries, namely that EU/UE-flows dominate in accounting for the unemployment variation. Austrian females, however, show a higher share of IU/UI-worker flows accounting for unemployment variance, namely 53% compared to only 49% in the US, and 35% in the UK. In Austria, men's and women's in- and outflows contribute almost equally to the variance of unemployment, a fact which is not the case in the US or the UK. In contrast, in these countries the outflow contributions account for a much higher share of the variance (55% to 61%), which is especially true for females (around 60%). The more pronounced role of IU/UI-flows – especially for females – potentially reflects differences in gender roles or welfare-regimes. More research in this direction is necessary.

Table 1: Decomposition of the overall and the gender specific unemployment rate - comparing Austrian data with the literature

	Austria			RS 2016[1] US			RS 2016[1] UK			EHS 2015[2] US
	Total	Male	Female	Total	Male	Female	Total	Male	Female	Total
EU	27	34	16	20	26	15	25	31	16	25
IU	20	14	33	17	15	24	8	6	11	12
UE	29	27	31	39	37	34	36	32	38	43
UI	25	25	20	22	19	25	19	15	24	17
EI	2	2	2	−2	−1	−3	−1	−1	−1	−1
IE	0	1	0	3	2	4	3	2	5	1
Residual	−3	−2	−1	1	1	2	10	16	6	3
UI/IU	45	39	53	39	34	49	27	21	35	29
EU/UE	56	61	47	59	63	49	61	63	54	68
EI/IE	2	3	2	1	1	1	2	1	4	0
EU/IU	47	48	49	37	41	39	33	37	27	37
UE/UI	54	51	51	61	56	59	55	47	62	60

Remarks: [1]*RS 2016 is Razzu and Singelton (2016), the reported results are the element f_{ij} found in Table 2 at page 139 (US: June 1990-August 2015, UK: 1997Q3-2015Q2).* [2]*Results from Table 3 in Elsby et al. (2015, pg. 74), 'DeNUNified' series starting 1978.*

4 Gender contributions to the unemployment rate

In the previous section we have concentrated on gender-specific results on unemployment for men and women separately. However, the result do not inform on the relative importance of each gender for overall unemployment fluctuations. In this section we, therefore, extend the framework of Elsby et al. (2015) to account for each gender's contribution to the variation of the total unemployment rate. We aim to answer the question, if men or women are more important for the fluctuations of the overall unemployment rate, and whether there are differences in the importance of single worker flows?

To study differences in the contributions of each gender $\mathbf{\Delta C_t}^{ij,s}$ with sex $s \in \{m, f\}$ to overall labor market stocks $\mathbf{s_t}$, we disaggregate the stocks (E_t and U_t) into subgroups for males and females $\mathbf{s_t} = \alpha_t \mathbf{s_t^m} + (1 - \alpha_t)\, \mathbf{s_t^f}$, while gender specific stocks are normalized to their respective population, and α_t is the share of group m in total population[10]. Equation (7) can easily be written for each specific subgroup s, whereas we have to assume $\alpha_t = \alpha_{t-1}$ to arrive at $\mathbf{\Delta s_t} = \alpha_t \mathbf{\Delta s_t^m} + (1 - \alpha_t)\, \mathbf{\Delta s_t^f}$. Due to the additive form, subgroup-specific contributions $\mathbf{\Delta C_t}^{ij,m}$ and $\mathbf{\Delta C_t}^{ij,f}$ can then easily be used to decompose variation in total stocks. However, as we aim to decompose the unemployment *rate* which is "normalized" by the labor-force rather than the total population, we have to use β as the share of males in labor-force instead. Then, we can write $\Delta u_t = \beta_t \Delta u_t^m + (1 - \beta_t)\, \Delta u_t^f$, again assuming $\beta_t = \beta_{t-1}$, and using (9) for the gender-specific unemployment rates.

Decomposing the variance of the total unemployment rate or the one for each gender separately is similar, but the later does not allow to draw any conclusion on the relative importance of each gender. The difference between both aproaches are cross-correlations between the series of each gender when accounting for total unemployment variation. Looking at each gender separately nets out these correlation between genders, and does not allow to evaluate the relative importance of each gender to overall unemployment variation. Later in the paper, we show both approaches to ensure that potentially significant cross-correlations are not responsible for the results.

Table 2 presents the results of the decomposition exercise for various cohorts. We fix β_t at its time-mean to "shut-down" the variation of the population share[11].

[10] The results of this extension depend on the size of each subgroup. This means interpretation of the results, i.e. evaluating the relative importance of either group in contributing to the overall unemployment dynamics. However, male/female group sizes are almost 0.5, with very little time variation.

[11] The same exercise is repeated with β_t allowed to vary over time. The results do not change significantly, and are reported in the Appendix.

To interpret the results adequately, the table also presents the respective share of males in the labor-force β. If β is high, we would also expect a high fraction of variance accounted for by males.

Starting with the whole working-age population (aged 15-64 years), 59% of total unemployment variation is accounted for by unemployment fluctuations of males. Concentrating on the prime-age cohort only (25-49 years old), males' variation account for almost three quarters of total unemployment variation. This finding is consistent with the recent evidence for the US and UK found in Razzu and Singelton (2016), who point to a higher cyclicality of males' EU-flows. Indeed, the Austrian labor market seems to be similar in this respect, as men's EU-flows contribute over-proportionally. However, also men's UI-flows contribute over-proportionally – especially when we look at the prime-age cohort – pointing to the fact that labor market attachment of males may be pro-cyclical. These aggregated findings are complementary to the results found in the studies of Peiro et al. (2012), Wood (2014), and Albanesi and Sahin (2017). They start their work by the observation of stronger variation in males job-losses during recessions and stronger employment growth afterwards, which typically concerns EU-flows.

Besides these typically studied cohorts, there is no evidence on the cohorts of the elderly (aged 50-64 years) or the youth (15-24 years old). Turning to the older cohort first, we see that it is characterized by a higher share of males (around 60%), which does not be related to the differences in retirement ages (retirement is measured as inactivity). Hence, the higher share of variance accounted for by males is clearly due to the higher weight in this cohort. There are no big differences between men and women with respect to specific worker-flows, with the exception of the flows between E and U (EU). They seem to be over-proportionally important for females. This is plausible for the Austrian case and might represent a gradual transition from employment into retirement via a phase of unemployment. As mentioned above, the Austrian retirement-scheme may have an asymmetric effect on the cyclicality of job-exit and retirement-entry, if an unemployment spell lays in between. While job-losses (EU) of older women may by cyclical, retiring (UI) may not. Eligibility for retirement depends on the demographic- and working-age, as well as on the existance of private pension-funds, or the willingness to accept pension-cuts in case of early retirement. All these reasons may not be cyclical. Turning the focus to the youth cohort, females interestingly account for around 56% of overall youth unemployment variation, which is not driven by the share β. This is surprising, given the dominance of males' contributions in all the other cohorts. Another interesting observation is that inflow-contributions (EU, IU) seem to have a higher relevance for males, whereas females contribute more through outflow components (UE, UI).

Table 2: Gender-specific contributions to the overall unemployment rate in Austria

	Youth (15-24 years)			Working-age (15-64 years)			Prime-age (25-49 years)			Elderly (50-64 years)		
	Total	Male	Female	Total	Male	Female	Total	Male	Female	Total	Male	Female
β	100.0%	52.9%	47.1%	100.0%	53.5%	46.5%	100.0%	52.8%	47.2%	100.0%	56.0%	44.0%
Var-Share	91.8%	36.2%	55.6%	103.0%	59.0%	44.0%	107.9%	71.6%	36.2%	102.4%	60.2%	42.2%
EU	26.8	15.0	11.8	27.2	19.5	7.7	28.1	20.3	7.8	14.6	6.9	7.7
IU	20.7	9.4	11.4	19.6	8.8	10.8	20.7	14.5	6.2	29.6	17.8	11.7
UE	20.9	5.9	15.1	29.1	14.2	14.9	18.7	6.7	12.0	21.0	12.5	8.5
UI	23.2	6.6	16.6	24.8	14.4	10.4	39.0	28.5	10.5	31.8	19.0	12.8
EI	1.1	0.1	1.0	1.9	1.5	0.5	1.4	0.5	0.8	2.1	1.7	0.4
IE	−0.9	−0.7	−0.3	0.3	0.6	−0.3	0.0	1.0	−1.0	3.4	2.2	1.2
Residual	8.2			−3.0			−7.9			−2.4		
UI/IU	43.9	16.0	27.9	44.4	23.2	21.2	59.7	43.0	16.6	61.3	36.8	24.5
EU/UE	47.7	20.9	26.9	56.3	33.7	22.6	46.8	27.1	19.7	35.5	19.4	16.1
EI/IE	0.2	−0.6	0.8	2.2	2.1	0.1	1.4	1.5	−0.2	5.5	4.0	1.6
Inflows	47.5	24.4	23.1	46.9	28.3	18.6	48.8	34.9	14.0	44.1	24.7	19.4
Outflows	44.1	12.4	31.7	53.9	28.6	25.3	57.7	35.2	22.4	52.7	31.5	21.3

Remarks: Variance decomposition acc. to (3) *of changes in the unemployment rate.* β *is the share of males in the labor-force, and is fixed at its time-mean. Based on Mikrozensus AT 2005Q1-2016Q4, own calculations.*

To eliminate the possibility that the contributions are driven by the elimination of the variation in the gender-shares (β_t), we report the results for the youth cohort again and allow β_t to vary over time (Table 3)[12]. Allowing β_t to vary does not change our results qualitatively, which is not much of a surprise as the share of males in the labor-force typically varies only slowly.

Our findings – especially those for the youth cohort – remain qualitatively the same if we consider the decomposition results of the gender specific unemployment rates (Table 8 in the Appendix). The re-emergence of major conclusions in the gender-specific context adds support to our findings above. Summarizing shortly the findings in Table 8, the male youth unemployment-rate is majorly driven by the employment-unemployment margin (EU/UE-flows), whereas for females the participation and employment margin is equally important. For the working-age population, women's unemployment variation is more driven by the participation margin, while men's employment margin is more important. When considering the group of 50-64 years aged the results indicate that the importance of the UI/IU-flows stems solely from the group of the elderly. The employment margin becomes less important for males when they get older, again, an indicator for a stepwise transition to retirement, and weak re-employment chances in case of a job-loss.

5 Robustness

The results presented above may not be related to business cycle variation, but to other reasons, which cause worker flows to be cyclical. Also, there could be several alternative explanations why we observe the gender-specific pattern of unemployment dynamics. Therefore, in this section we perform several robsutness checks. We concentrate on the results for the young cohort as they are a novel piece of evidence in the literature. First, we ask whether the cyclicality of UI and IU flows is the result of misclassification of U and I. We further check if the gender-specific conclusions may be a result of gender-specific demographic developments that spuriously introduce business cycle variation. Related to that, we evaluate the extent of a composition effect over the cycle. Over the business cycle, the characteristics of unemployed change and – as different people might have different individual transition probabilities – therefore the average probability to transit in or out of unemployment. Especially, Elsby et al. (2015) have shown that composition is a significant part of the cyclical pattern in UI-flows. However, we will conclude that our empirical findings are robust against

[12] In the Appendix we provide the equivalent of Table 2 using a time-varying β_t

Table 3: The effect of β on contributions to youth unemployment

	Memo item: β-constant			β-varying		
	Total	Male	Female	Total	Male	Female
β	100.0%	52.9%	47.1%	100.0%	52.9%	47.1%
Var-Share	91.8%	36.2%	55.6%	92.0%	36.1%	55.9%
EU	26.8	15.0	11.8	26.9	15.0	11.9
IU	20.7	9.4	11.4	20.7	9.3	11.4
UE	20.9	5.9	15.1	21.0	5.8	15.2
UI	23.2	6.6	16.6	23.2	6.5	16.7
EI	1.1	0.1	1.0	1.1	0.1	1.0
IE	−0.9	−0.7	−0.3	−0.9	−0.7	−0.2
Residual	8.2			8.0		
UI/IU	24.3	6.7	17.6	24.3	6.6	17.7
EU/UE	47.7	20.9	26.9	47.9	20.8	27.1
EI/IE	19.8	8.7	11.1	19.8	8.6	11.2
Inflows	27.9	15.1	12.8	28.0	15.1	12.9
Outflows	44.1	12.4	31.7	44.2	12.3	31.9

Remarks: Variance decomposition acc. to (3) *of changes in the unemployment rate, youth aged 15-24 years. Memo item is identical to those in Table 2. All cohorts are presented in the appendix. Based on Mikrozensus AT 2005Q1-2016Q4, own calculations.*

these issues.

5.1 Distinguishing unemployment from inactivity

Estimating gross worker flows may be problematic as they are prone to measurement error (classification errors) of labor market states[13]. If misclassification is an issue varying at business cycle frequencies, it renders worker flows cyclical independent from the business cycle (Abowd and Zellner 1985; Poterba and Summers 1984; Poterba and Summers 1986). Smith (2011) and Fujita and Ramey (2009) show that classification errors do not affect their results and conclude that the errors are not cyclical. Elsby et al. (2015) who treat this issue more thoroughly, conclude that errors especially affect transitions between unemployment and inactivity[14].

[13] The literature has further dealt with recall errors in case of retrospective survey data either by using additional administrative sources, or by using additional survey information (e.g. Magnac and Visser 1999; Hairault et al. 2015). However, recall errors are not an issue for our case here, as we do not use retrospective information.

[14] Another source of measurement errors is the high share of proxy interviews for young people. Especially marginal employment beside education may lead to imprecise answers

A potential source of cyclical measurement errors is a rather passive job-search behavior (low search intensity) of the youth in contrast to older cohorts. As unemployment is defined according to ILO (1982), *passive* job-search behavior blurs the border between unemployment and inactivity. For this reason, Clark and Summers (1982) have lumped job-search and inactivity together into a group of non-employed people. Numerous studies have examined this issue more closely and concluded that ILO-unemployment and inactivity are behavioral distinct states (Flinn and Heckman 1983; Jones and Riddell 1999; Brandolini et al. 2006). Jones and Riddell (1999) have identified an intermediate "waiting"-group of people which is behaviorally close to the group of unemployed. Brandolini et al. (2006) emphasized the importance of passive search for later employment outcomes. However, nothing specific has been said about the job-search behavior of the youth[15].

Drawing on the idea of Elsby et al. (2015), we purge our raw-data by recoding $U-I-U$- and $I-U-I$-transition patterns of individuals with at least three consecutive interviews to continuous spells of unemployment and inactivity, respectively[16]. After that, we recalculate the complete analysis. Results for the gender-specific contributions (the equivalent to Table 2) are reported in Table 4. Results are not changing by much, hence we consider them as robust against measurement errors.

5.2 Cohort size and demographic shifts

The development of the youth-cohort size can be a potential source of spurious correlation with the business cycle or the youth unemployment rate. Korenman and Neumark (2000) and Bertola et al. (2001) have identified a positive association between youth cohort size and youth unemployment, while Shimer (2001)

and erroneous coding between employment and inactivity. However, the IE/EI-dimension is practically irrelevant in our context.

[15] There is a small but serious literature on the choice of job-search methods and their effectiveness on unemployment exit rates of the youth (see e.g. Holzer 1987). However, this literature does not inform us about the dependencies of the youth' choice on the business cycle nor does it allow to draw conclusions on the youth' search intensity that would enable us to interpret the borderline between unemployment and inactivity (non-search) better.

[16] Elsby et al. (2015) use other methods for error adjustment: a method of Abowd and Zellner (1985) who use a small sample which is re-interviewed each month, and extensions based on Poterba and Summers (1986). Both methods are not applicable in our case. Additionally, there are limitations and drawbacks with our approach: It is necessary to compare at least three consecutive interviews (not only two as in the above case) which might introduce another source of attrition bias. Furthermore, the labour force survey consists of up to five consecutive interviews. In such a case, identifying $U-I-U$- and $I-U-I$-transitions is an arbitrary task, as e.g. $U-I-U-I-U$ could be recoded to either a continuous unemployment spell or to a $U-I-I-I-U$-transition pattern. In our case, we took the latter, but the results do not change by much if we take the first alternative.

Table 4: Worker flows corrected for mis-classification: contributions to youth unemployment

	Memo item: Not recoded			UIU/IUI-recoded		
	Total	Male	Female	Total	Male	Female
β	100.0%	52.9%	47.1%	100.0%	52.9%	47.1%
Var-share	91.8%	36.2%	55.6%	91.0%	34.6%	56.4%
EU	26.8	15.0	11.8	26.2	14.8	11.4
IU	20.7	9.4	11.4	20.3	8.9	11.4
UE	20.9	5.9	15.1	20.2	4.9	15.3
UI	23.2	6.6	16.6	24.3	6.6	17.7
EI	1.1	0.1	1.0	−0.9	−0.5	−0.4
IE	−0.9	−0.7	−0.3	0.8	−0.2	1.0
Residual	8.2			9.0		
UI/IU	43.9	16.0	27.9	44.6	15.5	29.1
EU/UE	47.7	20.9	26.9	46.4	19.7	26.7
EI/IE	0.2	−0.6	0.8	−0.1	−0.6	0.6
Inflows	47.5	24.4	23.1	46.6	23.7	22.9
Outflows	44.1	12.4	31.7	44.5	11.5	33.0

Remarks: Variance decomposition acc. to (3) *of changes in the unemployment rate, youth aged 15-24 years. Memo item is identical to those in Table 2. β is the share of males in the labor-force, and is fixed at its time-mean. UI/IU-transitions adjusted for mis-classification. Based on Mikrozensus AT 2005Q1-2016Q4, own calculations.*

has shown a negative relationship on US-state level. Figure 1 shows that youth population (aged 15-24 years) stayed relatively stable until 2013, but has been fallen sharply since then. This fall is reverting partly after 2016 through male population only. The demographic shifts after 2014 may introduce a cohort effect into our analysis. To test for this issue, we excluded the periods 2014-2016 from our variance decomposition. Overall, the results as shown in Table 5 remain qualitatively the same. Most significantly, the contribution of UI-flows - the most single important contribution for women - decreases from 21 to 16 percent. The share of variance explained by women's transitions decreases a bit, while EU/UE-transitions increase insignificantly.

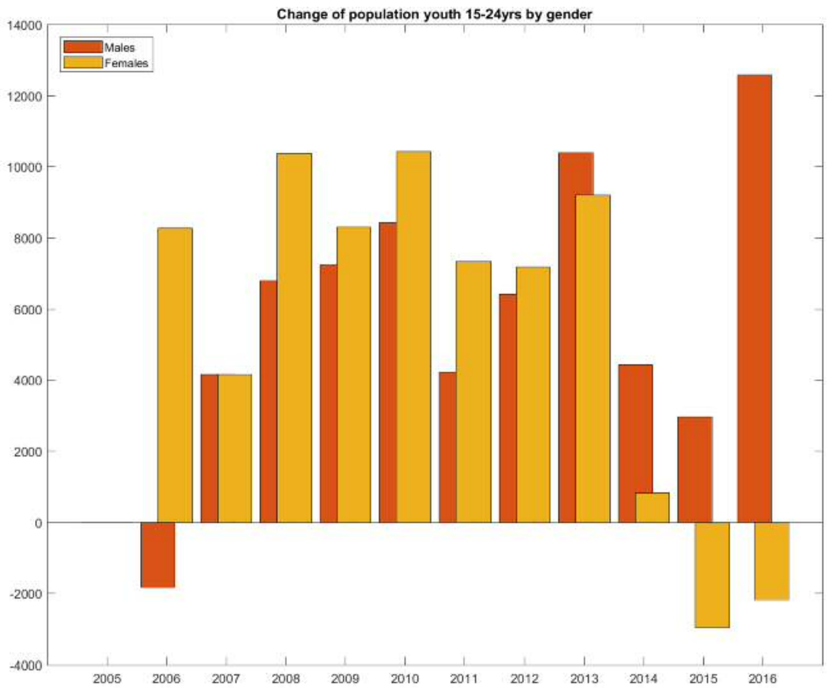
Another pitfall related to demography is the fact that we excluded men in military and civil service, who would have been treated as inactive. By excluding males in military and civil service, we exclude transitions from and to inactivity and may expect to underestimate IU and IE transitions. If men's cohort size to vary over time similar to the cycle, we may introducing a cyclical pattern into

Table 5: The impact of demographic shifts on contributions to youth unemployment

	Memo item: 2005-2016			2005-2013		
	Total	Male	Female	Total	Male	Female
β	100.0%	52.9%	47.1%	100.0%	52.9%	47.1%
Var-Share	91.0%	34.6%	56.4%	94.2%	38.9%	55.2%
EU	26.2	14.8	11.4	30.1	18.2	11.9
IU	−0.9	−0.5	−0.4	19.4	7.3	12.2
UE	20.2	4.9	15.3	23.2	7.7	15.5
UI	24.3	6.6	17.7	20.0	6.0	14.0
IE	0.8	−0.2	1.0	0.0	0.2	−0.2
EI	20.3	8.9	11.4	1.4	−0.4	1.8
Residual	9.0			5.8		
UI/IU	25.1	6.4	18.7	20.0	6.1	13.8
EU/UE	46.4	19.7	26.7	53.4	26.0	27.4
EI/IE	19.5	8.5	11.0	20.9	6.9	14.0
Inflows	27.0	14.6	12.4	30.1	18.4	11.7
Outflows	44.5	11.5	33.0	43.2	13.7	29.5

Remarks: Variance decomposition acc. to (3) *of changes in the unemployment rate, youth aged 15-24 years. Memo item is identical to those in Table 2. β is the share of males in the labor-force, and is fixed at its time-mean. Based on Mikrozensus AT 2005Q1-2016Q4, own calculations.*

Figure 1: Population of people aged 15-24 years by gender (2005=0)



these flows through exclusion of serving men. For that reason, we kept all the people in military and civil service and coded them as inactive. Table 6 displays the original results from the variance decomposition and the updated ones. Indeed, the importance of men's contributions increase, as expected, mostly due to an increase in the importance of IU-transitions. However, the original message remains the same: Women are responsible for the bulk of overall unemployment variantion due to high shares of outflows from unemployment (UE, UI).

5.3 Compositional changes throughout the cycle

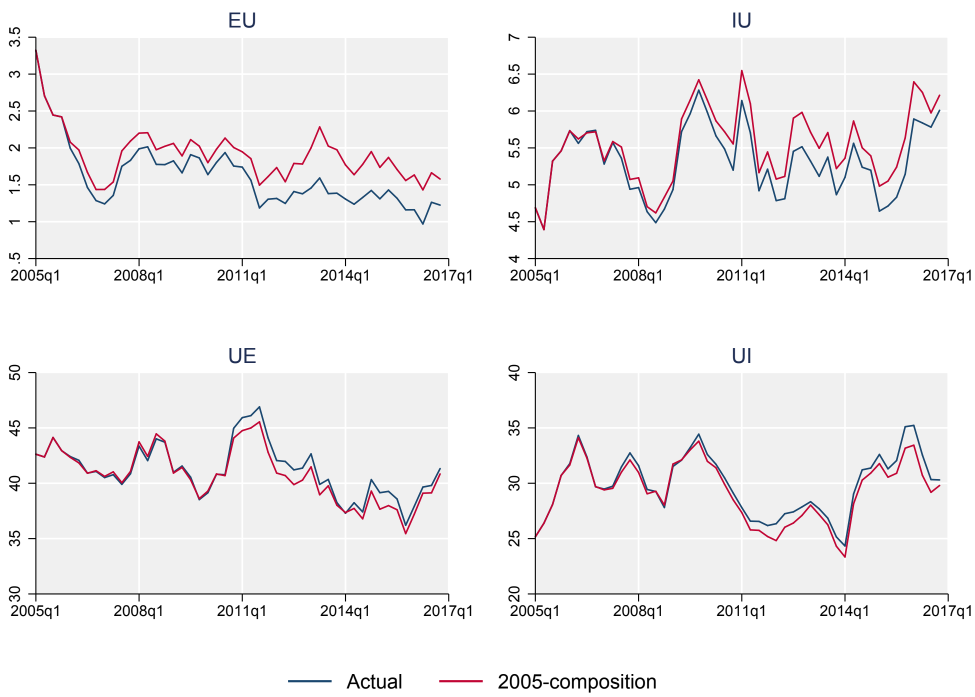
The composition of the pool of unemployed people change during the business cycle. Transition rates represent weighted averages of individual probabilities to transit. As a result, aggregate average transitions may either change through changing population-weights (i.e. different individuals with different characteristics and transition probabilities), or due to changing individual transition probabilities. Darby et al. (1985) and Baker (1992) show for the US that compositional changes over the cycle lead to the observed cyclicality of aggregated transitions. Shimer (2012) and Elsby et al. (2015) also conclude that

Table 6: Contributions to youth unemployment including people in military service

Military service	Gender	Share	EU	IU	UE	UI	EI	IE
Excluded	Males	36.1%	15.04	9.29	5.79	6.54	0.10	−0.66
	Females	55.9%	11.87	11.39	15.23	16.67	1.02	−0.24
Included	Males	39.5%	13.93	13.87	5.53	6.71	0.51	−0.01
	Females	51.9%	9.82	10.67	14.37	16.46	1.50	−0.32

Remarks: Based on Mikrozensus AT 2005Q1-2016Q4, own calculations. Military and civil service ("Praesenz-/Zivildienst") is coded as inactive.

Figure 2: Comparison of actual and counter-factual transitions based on 2005-characteristics



heterogeneity is non-negligible but that it explains only a minor fraction of the business cycle variation in unemployment. In their studies, they stratify aggregate transitions λ_{ij} into transitions of K-subgroups, indexed by (lowercase) k: $\lambda_{ij} = \sum \omega_k \lambda_{ij,k} \in K$. The overall transition rate is a weighted average of the groups' transition rates, with ω_k being the share of group k in the initial stock i. They have chosen a small set of individual characteristics and calculate transition rates for each cell of a full interaction of these characteristics.

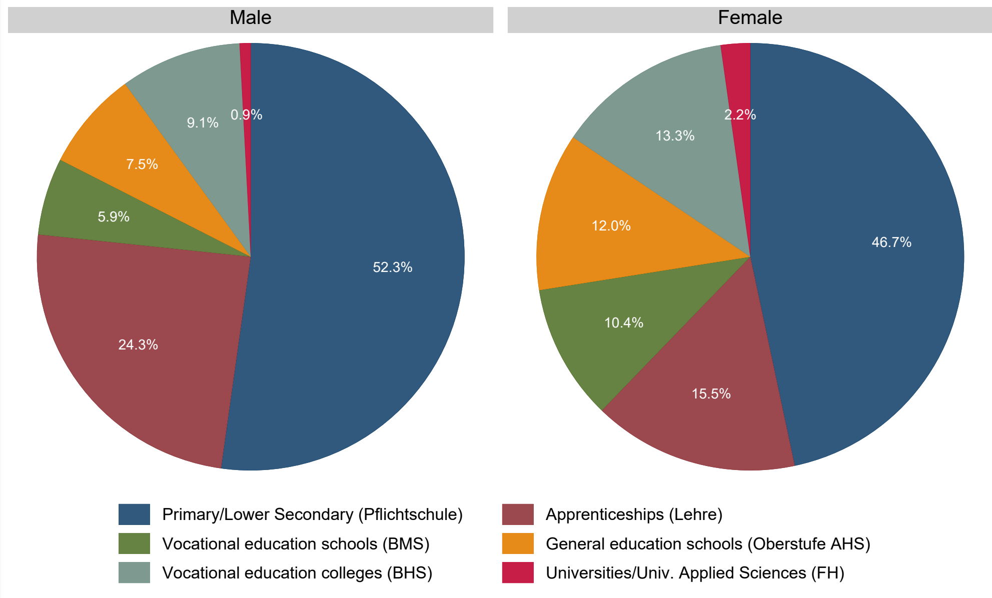
To "test" the potential effect of heterogeneity among the unemployed, we do not follow their approach as the number of observation for a thorough stratification is too low in our context. Instead, we estimate linear probability models for each transition and quarter, including controls for family background, job-loss (if applicable) as a proxy for the propensity to exit labor force as a discouraged worker, education (enrollment and attainment), temporary contracts, and gender and age[17]. For each quarter, we then predict individual probabilities and counter-factual probabilities for the observed distribution of characteristics in the year 2005. To obtain aggregate transition rates, we average the individuals' probabilities[18].

Figure 2 reports the results and compares the predicted probabilities with the counter-factual distribution in 2005. For all transitions, compositional shifts are rather small or invisible. We, therefore, are more in line with Shimer (2012) who does not find composition effects for unemployment in- and out flow transitions over the cycle. However, we contradict with Elsby et al. (2015) who have shown that a large part of the drop of UI-transitions in recessions comes from compositional shifts towards people with low UI-transition probabilities. The differences are clear: They analyze *total* unemployment and control for age only through the inclusion of a youth-category (16-24 years). Therefore, their results just showed that compositional shifts are significant for the whole working-age population, but does not capture potential heterogeneity *within* the youth. To sum up, we can conclude that our results can be interpreted cyclical effects of individual transition probabilities rather than as shifts in composition.

[17] Family background is defined by the education of the mother or father if available. Most, but not all youngsters live at home with their parents, and the survey only allows observing the parental characteristics for those living at home. Except age and sex, all variables are used in the regressions if applicable, e.g. temporary contract in transition where employment is involved, etc.

[18] For predicting the counter-factual, we take quarterly-specific characteristics of 2005, i.e. take 2005Q1-observations to predict Q1-transitions, and so on. This is to capture the strong seasonality of the Austrian labour market better. However, choosing a specific quarter does not alter the results or increase the composition effect.

Figure 3: Educational attainment by gender



6 Discussion

The previous sections have shown that the dynamics of the Austrian youth unemployment (i) are also significantly driven by transitions along the participation margin (UI, IU), (ii) are dominated by women's contributions as their fraction amounts to about 56%, (iii) are characterized by the fact that men contribute most through inflows to unemployment (EU, IU), and (iv) women by their outflow transitions (UE, UI). While we have already discussed (i) earlier, the other findings need some economic reasoning.

In this section, we provide an intuitive explanation of the gender-specific results which we think are related to the early gender segregation in temporal contracts and formal education present in the Austrian labor market. This argument is similar to the one put forward in the works of Wood (2014), Peiro et al. (2012), and Albanesi and Sahin (2017) which point to the importance of the occupational segregation between working-age men and women. However, we want to stress that this section does not claim either to be a complete review nor to develop a thorough theoretical model. But, it definitely points to the importance of further empirical and theoretical research on unemployment dynamics and worker flows.

6.1 Why are women's contributions that important?

Two specifics of the Austrian youth-labor market may be responsible for this finding. First, men attend in apprenticeships more often than women do. Many of them start their career as craftsmen, while women tend to attain higher formal education, as shown in Figure 3. Yet, apprenticeships are temporary employment arrangement including general practical training[19]. This is reflected by a higher fraction of temporary contracts among men than women (41 percent compared to only 34 percent). Due to the higher employment protection during the apprenticeships, men's worker flows between employment and unemployment might be less cyclical compared that of women's.

Second, men start working earlier in their lives than women do. Employment rates for male and female youngsters aged 15-19 years (15-24 years) are 42.5 and 31.8 (56.3 and 49.7), respectively. In turn, men have accumulated some savings during their employment period (e.g. entitlement to unemployment benefits). Higher savings may cause a lower search intensity after job loss or may reduce the acceptance rate of job offers[20]. Both cases may render the unemployment duration less cyclical (i.e. a lower correlation between unemployment and the business cycle). Hence, these arguments might be responsible for the observation that men's contributions to the overall unemployment variation in the youth cohort are less important than women's.

6.2 Females' outflow and males' inflow importance

The higher incidence of temporary contracts among men might also cause job-losses (inflows into unemployment) to be relatively more cyclical than job-findings (outflow out of unemployment). For example, if the term-contract ends during a recession, young men might more likely loose their jobs while they would transit to a permanent contract during a boom more often (i.e. stepping-stone effect). Hence, it is plausible to observe a higher share of unemployment variance that is explained by inflow-contributions of males.

Indirect evidence for this argument may be found in OECD (2009) and Scarpetta et al. (2010). Although they do not elaborate on worker flows, they have indicated that the dis-continuation of temporary contracts in recessionary

[19] Apprentices are fixed-term employment contracts subject to high subsidies (i.e. low compensation and the provision of public schools) and strong regulation on a sectoral level (e.g. employment protection).

[20] Eckstein and Wolpin (1995) estimated offer and acceptance rates for the first job after school for youngsters in the US. More schooling translates in higher acceptance rates. However, nothing can be said on the cyclicality of these rates.

times may partly drive youth unemployment experience across OECD countries. Moreover, direct evidence on the stepping-stone effect presented by the literature (i.e. that is estimating a positive effect of temporary work on the probability to find a permanent job) is in favour of our argument. For the UK, Booth et al. (2002) report a significant stepping-stone effect. For Spain, Guell and Petrongolo (2007) report a negative impact of the cycle on conversion probabilities from fixed-term contract to permanent ones. Both papers give some support to our argument[21]. A cyclical conversion probability, which hits men more than women may explain the importance of inflows into unemployment among men.

It remains to be explained, why women contribute more by their outflow-transitions. Recall that we have seen in Figure 3 that young women have higher formal education compared to their male counterparts. If education is a pull-factor for further education, women drop out of the labour force more likely for further education or training (Choi et al. 2014). If this pull-factor is sensitive to the business cycle (i.e. re-employment prospects), then women respond with an increased probability to exit the labour force. This is consistent with the finding that the UI-contribution is much more important.

Educational segregation may introduce another channel determining our results. Cairó and Cajner (2017) have developed a model of complementaries between formal education and on-the-job training (match-specific human capital). The match-specific human capital increases the productivity of a match and reduces separation rates. Due to the higher (lower) level of formal education of women (men), they more (less) often acquire trainings and are therefore less (more) sensitive to separations. Job-finding rates, however, are dependent on the value of a vacancy, which in turn depends on training costs. In their model, these costs have two effects on vacancy-posting: a direct negative effect on the vacancy-value, and a positive one through a lower separation risk in the future. If the first is larger than the latter, and if we assume that training-costs for women are in general higher than for men – which is plausible as women typically apply to jobs with higher skill requirements than men(see e.g. Blat-

[21] Note that for the US, Autor and Houseman (2010) report that there is no stepping-stone effect at all. Givord and Wilner (2014) give evidence for the existence of a stepping-stone effect in France and show that this effect increases in recessions. This would run against our argumentation, however, the results are highly France-specific. Givord and Wilner (2014) state that the existence of the large share of temporary agency workers may be used by firms for their flexibility needs, while fixed-term contracts may serve as a screening device. While employer reduce employment through the first pool of workers in recessions, the workers from the latter pool benefit from increased chances to convert their contracts. This is not a comparable institutional setting to Austria.

ter et al. 2012)[22] – then women will respond more sensitive on the job-finding side[23]. This is consistent with the observed high value of the UE-contributions.

7 Conclusion

We have used novel worker flow data for Austria to decompose the variance of the unemployment rate into contributions of single worker-flows. Moreover, we extended the empirical framework of Elsby et al. (2015) to arrive at gender-specific contributions to the overall unemployment rate. Our paper is related to a large literature on unemployment dynamics, and specifically adds further empirical evidence on important gender differences; a dimension only loosely studied so far. We showed that flows between unemployment and inactivity are more important for determining unemployment variation compared to previous works, but confirmed the need to incorporate the participation margin into models of unemployment dynamics. Furthermore, we found that women's contributions to the variation of the youth unemployment rate are dominating, a finding which contradicts the scarce evidence that typically males dominate unemployment variation over the business cycle. Moreover, female dominance is solely caused by flows out of unemployment, while men contribute over-proportionally through their inflows into unemployment.

After a thorough robustness section, we argued that educational segregation of young men and women in Austria might cause these results. The higher incidence of temporal contracts among young men, and the higher share of women with a formal degree, are a plausible explanation for our empirical findings. While a higher fraction of temporary contracts among men may render their unemployment experience less cyclical, it might, however, become more inflow dominated. For young women, a higher share of formal education may induce a higher cyclicality and a higher outflow-importance through complementaries between education and on-the-job training.

But are our results specific for Austria? Potentially yes, most plausibly not! Our work asks for further empirical research in other economies using our methodological extension of the variance decomposition technique of Elsby et al. (2015) and Razzu and Singelton (2016) to account for the gender dimension in

[22] If we assume that training costs incloude also recruiting costs, than these costs most likely depend positively on the skill requirements of the job (Blatter et al. 2012; Kramarz and Michaud 2010; Abowd and Kramarz 2003). This fits to the observation, that young women in Austria apply to occupations in industries with - on average - higher skill level.

[23] In Cairó and Cajner (2017), both effects are always equal, which is necessary to replicate their empirical fact that job-finding rates of educated and non-educated are almost equal.

overall unemployment dynamics. It further asks for more advanced theoretical models concentrating on structural differences within an economy in influencing business cycle dynamics of labor markets, such as the importance of the participation margin, or patterns of occupational or educational segregation.

From a policy perspective, our results are important in several respects. The importance of the participation margin asks for policies to keep labor market attachment high during downturns. The differences between gender and cohorts point to a more diversified policy mix, ranging from measures to tackle the highly cyclical employment of prime-age males, to re-employment policies targeted at older people, and gender-specific policies aiming to support the early carriers of young people. Our results also emphasize to look at both, cyclical as well as structural reasons for the development of the unemployment rate over the business cycle (rather than focusing on cyclical reasons only).

References

Abowd, J. and F. Kramarz (2003). "The costs of hiring and separations". In: *Labour Economics* 10.5, pp. 499–530.

Abowd, J. and A. Zellner (1985). "Estimating Gross Labor Force Flows". In: *Journal of Business and Economic Statistics* 3, pp. 254–283.

Albanesi, S. and A. Sahin (2017). "The Gender Unemployment Gap". In: *NBER Working Paper No. 23743* 08.

Autor, D. and S. Houseman (July 2010). "Do Temporary-Help Jobs Improve Labor Market Outcomes for Low-Skilled Workers? Evidence from 'Work First'". In: *American Economic Journal: Applied Economics* 2, pp. 96–128.

Baker, M. (1992). "Unemployment Duration: Compositional Effects and Cyclical Variability". In: *The American Economic Review* 82.1, pp. 313–321.

Barnichon, R. and A. Figura (2012). "Labor Market Heterogeneities and the Aggregate Matching". In:

Bell, D. and D. Blanchflower (2010). "Youth Unemployment: Déjà Vu?" In: *IZA discussion paper No. 4705*.

Bertola, G., F. Blau, and L. Kahn (2001). "Comparative Analysis of Labor Market Outcomes: Lessons for the US from International Long-Run Evidence". In: *The Roaring Nineties*. Ed. by A. Krueger and R. Solow. Russell Sage Foundaton The Century Foundation.

Blatter, M., S. Muehlemann, and S. Schenker (2012). "The costs of hiring skilled workers". In: *European Economic Review* 56.1, pp. 20–35.

Booth, A. L., M. Francesconi, and J. Frank (2002). "Temporary jobs: stepping stones or dead ends?" In: *Economic Journal* 112, pp. 189–213.

Brandolini, A., P. Cipollone, and E. Viviano (2006). "Does the ILO Definition Capture All Unemployment?" In: *Journal of the European Economic Association* 4.1, pp. 153–179.

Cairó, I. and T. Cajner (2017). "Human Capital and Unemployment Dynamics: Why More Educated Workers Enjoy Greater Employment Stability". forthcoming.

Castles, F. and H. Obinger (2008). "Worlds, Families, Regimes: Country Clusters in European and OECD Area Public Policy". In: *West European Politics* 31.1-2, pp. 321–344.

Choi, Sekyu, Alexandre Janiak, and Benjamín Villena-Roldán (2014). "Unemployment, participation and worker flows over the life-cycle". In: *The Economic Journal* 125.589, pp. 1705–1733. DOI: 10.1111/ecoj.12176.

Clark, K. and L. Summers (1982). "The Dynamics of Youth Unemployment". In: *The Youth Labor Market Problem: Its Nature, Causes and Consequences*. Ed. by R. Freeman and D. Wise. University Press of Chicago for NBER, pp. 199–234.

Darby, M., J. Haltiwanger, and M. Plant (1985). "Unemployment Rate Dynamics and Persistent Unemployment under Rational Expectations". In: *American Economic Review* 75.4, pp. 614–637.

Eckstein, Z. and K. Wolpin (1995). "Duration to First Job and the Return to Schooling: Estimates from a Search-Matching". In: *The Review of Economic Studies* 62.2, pp. 263–286.

Elsby, M., B. Hobijn, and A. Sahin (2013). "Unemployment Dynamics in the OECD". In: *Review of Economics and Statistics* 95.2, pp. 530–548.

— (2015). "On the importance of the participation margin for labor market fluctuations". In: *Journal of Monetary Economics* 72, pp. 64–82.

Elsby, M., R. Michaels, and G. Solon (2009). "The ins and outs of cyclical unemployment". In: *American Economic Journal: Macroeconomics* 1.1, pp. 84–110.

Elsby, M., J. Smith, and J. Wadsworth (2011). "The Role of Worker Flows in the Dynamics and Distribution of UK Unemployment". In: *IZA DP No. 5784*.

Esping-Andersen, G. (1990). *The three worlds of welfare capitalism*. Princeton University Press.

— (1999). *Social Foundations of Postindustrial Economies*. Oxford University Press.

Flinn, C. and J. Heckman (1983). "Are Unemployment and Out of the Labor Force Behaviorally Distinct Labor Force States?" In: *Journal of Labor Economics* 1.1, pp. 28–42.

Fujita, S. (2011). "Dynamics of Worker Flows and Vacancies: Evidence from the Sign Restriction Approach". In: *Journal of Applied Econometrics* 26, pp. 89–121.

Fujita, S. and G. Ramey (2009). "The Cyclicality of Seperation and Job Finding Rates". In: *International Economic Review* 50, pp. 415–430.

Givord, P. and L. Wilner (2014). "When does stepping-stone work? Fixed-term contracts versus temporary agency work in changing economic conditions". Journal of Applied Econometrics.

Gomes, P. (2012). "Labour market flows: Facts from the United Kingdom". In: *Labor Economics* 19.2, pp. 165–175.

Guell, M. and B. Petrongolo (2007). "How binding are legal limits? Transitions from temporary to permanent work in Spain". In: *Labour Economics* 14, pp. 153–183.

Hairault, J.-O., Th. Barbanchon, and Th. Sopraseuth (2015). "The Cyclicality of the Separation and Job-Finding Rates in France". In: *European Economic Review* 76, pp. 60–84.

Holzer, H. (1987). "Job Search by Employed and Unemployed Youth". In: *Industrial and Labor Relations Review* 40.4, pp. 601–611.

ILO (1982). "Resolution concerning statistics of the economically active population, employment, unemployment and underemployment". In: *adopted by the Thirteenth International Conference of Labour Statisticians*.

Jones, S. and W. Riddell (1999). "The Measurement of Unemployment: An Empirical Approach". In: *Econometrica* 67.1, pp. 147–162.

Korenman, S. and D. Neumark (2000). "Cohort Crowding and Youth Labor Markets: A Cross-National Analysis". In: *Youth Employment and Joblessness in Advanced Countries*. Ed. by D. Blanchflower R. Freeman. University of Chicago Press, pp. 57–106.

Kramarz, F. and M.-L. Michaud (2010). "The shape of hiring and separation costs in France". In: *Labour Economics* 17.1, pp. 27–37.

Kudlyak, M. and F. Schwartzman (2012). "Accounting for Unemployment in the Great Recession: Nonparticipation Matters". In: *FED Richmond Working Paper No. 12-04*.

Magnac, Th. and M. Visser (1999). "Transition Models with Measurement Errors". In: *The Review of Economics and Statistics* 81.3, pp. 466–474. DOI: 10.1162/003465399558229.

Mortensen, D. and C. A. Pissarides (1994). "Job Creation and Job Destruction in the Theory of Unemployment". In: *Review of Economic Studies* 61.3, pp. 397–415.

OECD (2009). "OECD Employment Outlook 2009: Tackling the Jobs Crisis". In: *OECD Publishing*.

Peiro, A., J. Belaire-Franch, and M. Gonzalo (2012). "Unemployment, cycle and gender". In: *Journal of Macroeconomics* 34, pp. 1167–1175.

Petrongolo, B. and C. A. Pissarides (2008). "The ins and outs of European unemployment". In: *The American Economic Review* 98.2, pp. 256–262.

Poterba, J. and L. Summers (1984). "Response Variation in the CPS: Caveats for the Unemployment Analysis". In: *Monthly Labor Review* 107, pp. 37–43.

— (1986). "Reporting Errors and Labor Market Dynamics". In: *Econometrica* 54, pp. 1319–1338.

Razzu, G. and C Singelton (2016). “Gender and the business cycle: An analysis of labour markets in the US and UK”. In: *Journal of Macroeconomics* 47, pp. 131–146.

Scarpetta, S., A. Sonnet, and T. Manfredi (Apr. 2010). “Rising youth unemployment during the crisis: how to prevent negative long-term consequences on a generation?” In: *OECD Social, Employment and Migration Working Paper No. 6*.

Schoiswohl, F. and M. Wüger (2016). “A Representative Matched Cross-section Survey for Austria - Measuring Worker Flow Dynamics with the Austrian Labour Force Survey”. In: *Department of Economics Working Paper Series* 223.

Shimer, R. (2001). “The Impact of Young Workers on the Aggregate Labor Market”. In: *Quarterly Journal of Economics* 116.3, pp. 969–1007.

— (2012). “Reassessing the ins and outs of unemployment”. In: *Review of Economic Dynamics* 15, pp. 127–148.

Smith, J. (2011). “The Ins and Outs of UK Unemployment”. In: *The Economic Journal* 121.552, pp. 402–444.

Statistik Austria (2016). *Mikrozensus Mikrodatensï¿½tze 2004Q1-2016Q4*.

Wood, C. (2014). “The rise in women’s share of nonfarm employment during the 2007-2009 recession: a historical perspective”. In: *Monthly Labor Review* 04.

Table 7: Gender-specific contributions to overall unemployment rate

	Youth (15-24 years)			Working-age (15-64 years)			Prime-age (25-49 years)			Elderly (50-64 years)		
	Total	Male	Female	Total	Male	Female	Total	Male	Female	Total	Male	Female
β	100%	52.9%	47.1%	100%	53.5%	46.5%	100%	52.8%	47.2%	100%	56.0%	44.0%
Var-Share	92.0%	36.1%	55.9%	103.0%	58.9%	44.1%	108.2%	71.9%	36.3%	102.5%	60.5%	42.0%
EU	26.9	15.0	11.9	27.2	19.5	7.7	28.0	20.3	7.7	14.6	6.8	7.7
IU	20.7	9.3	11.4	19.7	8.8	10.9	20.8	14.5	6.3	29.9	18.1	11.8
UE	21.0	5.8	15.2	29.1	14.1	15.0	18.7	6.7	12.0	21.0	12.5	8.5
UI	23.2	6.5	16.7	24.8	14.3	10.5	38.9	28.4	10.5	31.6	19.1	12.5
EI	1.1	0.1	1.0	1.9	1.5	0.5	1.4	0.5	0.8	2.2	1.8	0.4
IE	−0.9	−0.7	−0.2	0.3	0.6	−0.3	0.0	1.0	−1.0	3.4	2.2	1.2
Residual	8.0			−3.0			−7.8			−2.5		
UI/IU	43.9	15.8	28.1	44.5	23.1	21.4	59.7	42.9	16.8	61.5	37.2	24.3
EU/UE	47.9	20.8	27.1	56.3	33.6	22.7	46.7	27.0	19.7	35.5	19.3	16.2
EI/IE	0.2	−0.6	0.8	2.2	2.1	0.1	1.4	1.5	−0.2	5.6	4.0	1.5
Inflows	47.6	24.3	23.3	46.9	28.3	18.6	48.8	34.8	14.0	44.4	24.9	19.5
Outflows	44.2	12.3	31.9	53.9	28.5	25.4	57.6	35.1	22.5	52.6	31.6	20.9

Remarks: Variance decomposition acc. to (3) of changes in the unemployment rate. β is the share of males in the population, and is allowed to vary over time. Based on Mikrozensus AT 2005Q1-2016Q4, own calculations.

Table 8: Contributions to gender-specific unemployment rates in Austria

	Youth (15-24 yrs.)		Working-age (15-64 yrs.)		Prime-age (25-49 yrs.)		Elderly (50-64 yrs.)	
	Male	Female	Male	Female	Male	Female	Male	Female
EU	32.6	19.9	33.9	16.0	30.4	20.5	15.7	16.9
IU	13.9	18.3	13.8	32.5	16.7	25.9	25.7	32.1
UE	30.2	21.5	26.9	31.3	14.3	24.8	19.3	13.4
UI	13.0	22.7	24.5	19.6	42.4	25.3	30.9	22.6
EI	−5.5	0.0	2.0	2.1	1.1	3.4	2.6	2.4
IE	−1.1	−0.7	1.0	−0.2	1.0	−2.0	3.1	−0.2
Resid	16.8	18.4	−2.3	−1.3	−5.9	2.0	2.6	12.8
UI/IU	26.9	40.9	38.4	52.2	59.1	51.2	56.7	54.7
EU/UE	62.8	41.4	60.9	47.3	44.6	45.3	35.0	30.3
EI/IE	−6.6	−0.7	3.0	1.8	2.1	1.5	5.7	2.2
Inflows	46.5	38.2	47.8	48.6	47.1	46.4	41.5	49.0
Outflows	43.3	44.1	51.5	50.9	56.7	50.1	50.3	36.0

Remarks: Variance decomposition acc. to (3) *of changes in the unemployment rate. Based on Mikrozensus AT 2005Q1-2016Q4, own calculations.*