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The Life-cycle Profile of Worker Flows in Lithuania

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ABSTRACT

We use survey micro-data for 31 European countries, and estimate the life-cycle profiles of worker transition probabilities across employment, unemployment and nonparticipation. The estimated transition probabilities are then used to explain aggregate difference in employment rates between Lithuania and Europe. We show that the separations from employment is a key in understanding differences in labor market outcomes of both genders, and that demographics play a large negative role for Lithuanian employment rates. The results have important implications for economic policies that are discussed at the end of the analysis.

Keywords: Employment, Unemployment, Labor Force Participation, Life cycle, Worker Flows, Labor Market Institutions.

JEL codes: E02, E24, J21, J64, J82.

1 Introduction

This paper uses survey micro-data and estimate the life-cycle profiles of worker transition probabilities across employment, unemployment and nonparticipation in Lithuania.[1] We show that labor market flows vary significantly over the life cycle. For both genders, job-loosing probability shows an increase until early 20s and then a steady decrease during the rest of the working life. Transition probabilities to non-participation both from employment and from unemployment portray stable patterns for prime-age individuals (those aged 25 to 54), while they show a negative slope at younger ages and an increase for older workers. The job-finding probability out of unemployment shows an increase until mid-20s and then a slight but persistent decrease. These findings are consistent with Choi et al. (2015) who use data from the Current Population Survey to study how worker flows shape the unemployment and participation rates in the U.S. labor market.

To assess the importance of each worker flow in accounting for each country's aggregate labor market outcomes, we develop a decomposition method that relies on a first-order Markov chain to link worker stocks and flows. The method allows us to decompose aggregate employment differences into the following three components: demographics, i.e. the composition of workers of different age in the population, initial conditions, i.e. the distribution of workers across different labor market states at the age of 16, and transition probabilities. The latter can be further decomposed into a contribution of each transition probability.

The estimated transition probabilities are then used to explain aggregate difference in employment rates between Lithuania and Europe. We show that separation from employment is a key in understanding differences in labor market outcomes of both genders, and that demographics play a large negative role for Lithuanian employment rates. The results have important implications for economic policies that are discussed at the end of the analysis.

The remainder of the paper is organized as follows. Section 2 presents the data and the measurement of the labor flows. Section 3 presents the estimated flows and fits a first-order Markov chain. Section 4 formalizes, presents and discusses the results of the decomposition. Section 5 concludes.

2 Data and Measurement

2.1 Data Sources

We use micro-data from the Statistics on Income and Living Conditions (EU-SILC) collected by Eurostat. The EU-SILC is an unbalanced household-level panel survey that collects comparable multidimensional annual micro-data on a few thousand households per country, starting in 2004. The dataset is particularly well suited for our study as it contains a retrospective calendar of the monthly labor force status (employment, unemployment, nonparticipation) of workers living

[1] See Lalé and Tarasonis (2018) for life-cycle profiles of worker flows in Europe.

in 29 European countries.[2] We add data for Germany by using recent waves of the German Socio-Economic Panel. We use the Swiss Household Panel to add data for Switzerland. Overall, our sample covers 31 countries over the period 2004-2016. Sample size varies depending on the country and ranges from 2,250 households in Malta to 5,750 households in the U.K. We end up with a total of 4,167,231 individual-year observations corresponding to 1,392,329 individuals in our final sample.

2.2 Measurement

Measurement error. We consider three labor force status: employment (E), unemployment (U) and non-participation (N). Measurement error is a potentially important concern, especially for flows between unemployment and non-participation. To address this issue, we develop an approach much in the spirit of Elsby et al. (2015) de-NUN-ification procedure.

We treat our data as being quarterly instead of monthly. Suppose for instance that we look at data from January (month 1) to June (month 6) for individual i. We define i's labor force status during the first quarter as her labor force status in February (month 2). Likewise, her status in the second quarter is taken to be that in May (month 5). If we observe the sequence NUN within the first (second) quarter, then we recode i's labor status in month 2 (5) as being N. We treat the sequence UNU in the same fashion, by recoding i's labor status in month 2 (or 5, if looking at the second quarter) into U.

Our procedure to deal with measurement error leaves the stocks and flows roughly unchanged in levels, and it increases the precision of our estimates.

Measuring transition probabilities. Letting $s_{i,a,t}$ denote the indicator function that takes the value of 1 if individual i's labor force status is $s \in \{E, U, N\}$ in period t, when i's age is a, and denoting by w_i the relevant (cross-sectional) survey weight of individual i, we calculate

$$S_{a,t} = \sum_i w_i s_{i,a,t}. \tag{1}$$

$S_{a,t}$ is the stocks of individuals of age a in period t whose labor force status is s. Likewise, we construct $F^{ss'}_{a,t}$, worker flows from labor force status s to status s' at age a in period t, based on age-specific individual indicator function$f^{ss'}_{i,a,t}$ that takes the value of 1 if individual i's labor force status is $s \in \{E, U, N\}$ in period t and $s' \in \{E, U, N\}$, $s \neq s'$, in period $t+1$, and using the relevant (longitudinal) survey weights.[3] We increase the precision of our calculations by using three-year bins centered on each age a. For instance, to calculate $S_{30,t}$, we pool data on individuals aged 29, 30 and 31 in period t. We proceed in the same fashion with respect to t,

[2]Austria, Belgium, Bulgaria, Croatia, the Czech Republic, Cyprus, Denmark, Estonia, Finland, France, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and the United Kingdom.

[3]In the EU-SILC, we do not have longitudinal weights tailored to our empirical exercise. Therefore we take the average of an individual's cross-sectional weights to construct longitudinal weights. The other micro-data sets we use provide longitudinal in addition to cross-sectional weights. In particular, for France and the United Kingdom, we compare the flows based on the longitudinal weights that we construct with those based on weights provided in the survey micro-data of the FLFS and UKLFS. We find no significant differences.

i.e. we pool data from $t-1$, t and $t+1$ to compute the period-t stocks and flows statistics.

Life-cycle profiles. Then, by taking the ratio between flows (F) and stocks data (S), we obtain estimates of quarterly transition probabilities across employment, unemployment and non-participation, $P^{ss'}_{a,t} = \frac{F^{ss'}_{a,t}}{S_{a,t}}$.

Next, to separate the effects due to the business cycle we extract the life-cycle profile of stocks and flows using a non-parametric approach by running the following regressions:

$$P^{ss'}_{a,t} = p^{ss'}_{a}\mathbf{D_a} + \psi_t\mathbf{D_t} + \varepsilon_{a,t}, \tag{2}$$

where $P^{ss'}_{a,t}$ is age-specific transition probability at time t, $\mathbf{D_a}$ ($\mathbf{D_t}$) is a full set of age (time) dummies and $\varepsilon_{a,t}$ is the residual of the regression. The life-cycle profile of a stocks or flows statistic refers to the coefficients $p^{ss'}_a$ on the age dummies. We use the same procedure to extract the life-cycle profile of individuals stocks, $S_{a,t}$.

Time aggregation. Finally, we clear the transition probabilities from time aggregation bias using the continuous-time adjustment procedure developed by Shimer (2012) and we store the adjusted, age-a quarterly transition probabilities in a matrix denoted as Γ_a:

$$\Gamma_a = \begin{bmatrix} p^{EE}_a & p^{EU}_a & p^{EN}_a \\ p^{UE}_a & p^{UU}_a & p^{UN}_a \\ p^{NE}_a & p^{NU}_a & p^{NN}_a \end{bmatrix}. \tag{3}$$

where the probabilities of staying in each state, p^{ss}_a, are calculated as the residuals given the estimated probabilities of transitioning out of a given state.

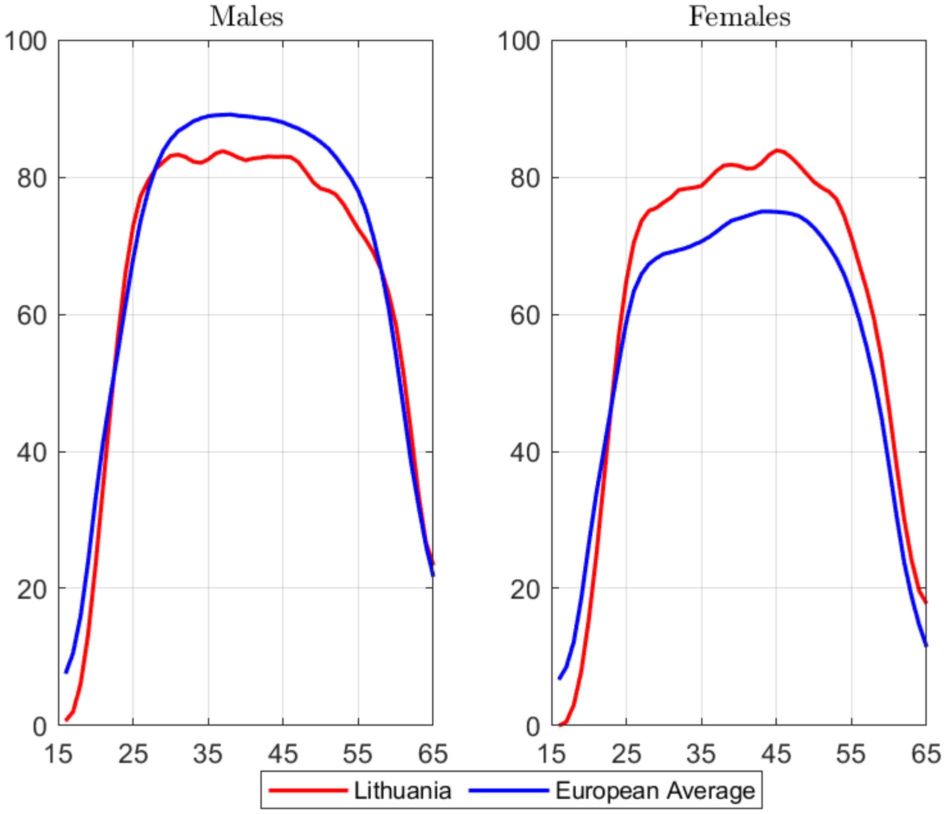
3 A First Look at the Data

3.1 Worker Flows

In Figure 1, we report the life-cycle employment profiles in Lithuania and Europe for the two genders. European average is calculated as a population-weighted average of all countries in the sample (see above). We can see that labor market experiences vary significantly over the life cycle: employment is low below age 25, it peaks during the prime age (25-54) and falls dramatically for workers above a certain age. Besides level differences, the male and female profiles are quite similar.

When it comes to the levels, the employment rate of Lithuanian men in their prime age is almost 10 p.p. lower than the employment rate of their European peers. Young and older workers portray quite similar employment rates in both regions. The conclusion is reversed for women: females in Lithuania portray significantly higher employment rates than in the rest of Europe and the difference remains positive, although smaller for older female workers as well. The result is mainly due to the striking variation in European gender employment gaps, ranging from 10 percentage points in the United Kingdom, and Scandinavian countries

Figure 1: Life-cycle employment rates in Lithuania and Europe: Males (left) and females (right)



Note: Authors' calculation on EU-SILC data. European average is a population-weighted average of all countries in the sample (see in the text).

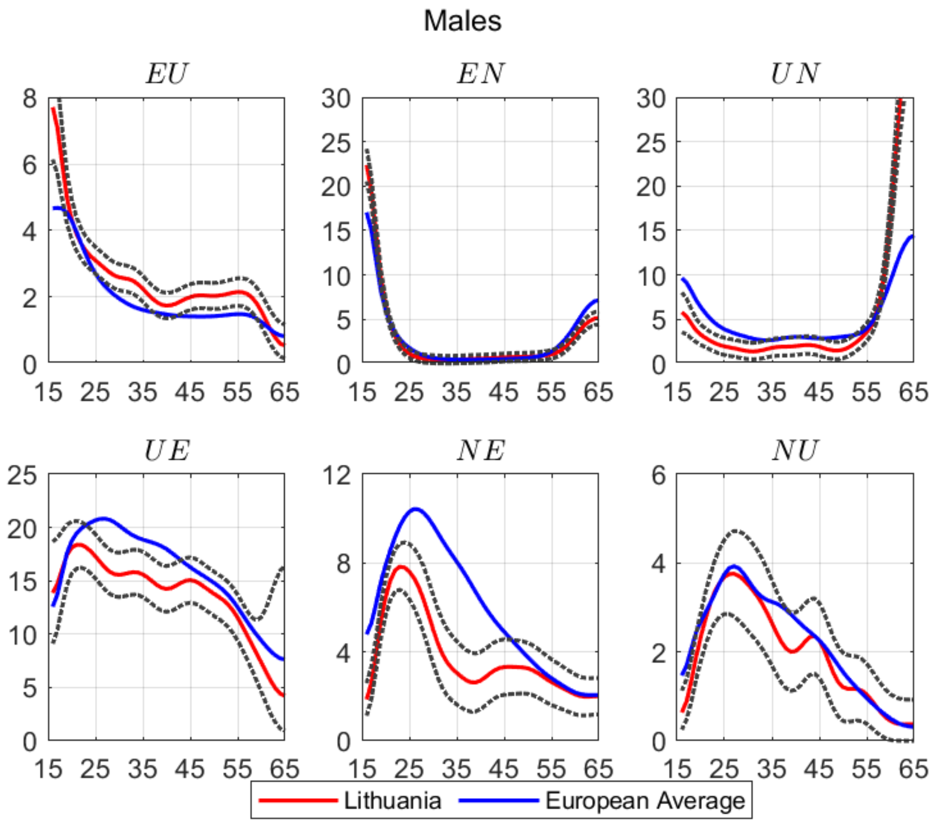
to 15–25 points in northern and central Europe, up to 30–40 points in southern Europe and Ireland (see Olivetti and Petrongolo (2008)).

Next, Figures 2 and 3 display the life-cycle transition probabilities between various labor market statuses respectively for men and women in Lithuania. Again, to give context to the country-specific estimates we plot them against the average life-cycle transition probabilities across all countries in our sample. Qualitatively, for both genders the employment-to-unemployment (EU), employment-to-nonparticipation (EN) and the unemployment-to-nonparticipation (UN) transition probabilities have stable patterns between 25 and 55 years of age, while they show a negative slope at younger ages and an increase for older workers. The job finding probability (UE) shows an increase until the mid-20s and then a slight but persistent decrease. The probabilities of going from nonparticipation to both employment and unemployment (NE and NU) show hump-shaped patterns, peaking in the mid-20s.

Looking at transition probabilities for men, we can see that Lithuanian males are facing a significantly higher probability of losing a job (EU) than workers in the rest of Europe. This is true especially for very young workers and for workers between 50 and 60 years of age. Job-finding probabilities out of unemployment (UE) are more similar except those between 25 and 45, where European workers are exiting unemployment at a faster rate.

Transitions from unemployment to nonparticipation (UN) increase dramatically at the age

Figure 2: Transition probabilities in Lithuania and Europe: Men



Note: Authors' calculation on EU-SILC data. European average is a population-weighted average of all countries in the sample (see in the text).

of 55 and the rate of change is larger than the European average. Interestingly, this occurs well before the statutory retirement age in Lithuania which is above 60. Lastly, job-finding out of nonparticipation (NE) in Lithuania appears to be also significantly lower for those aged between 20 and 50.

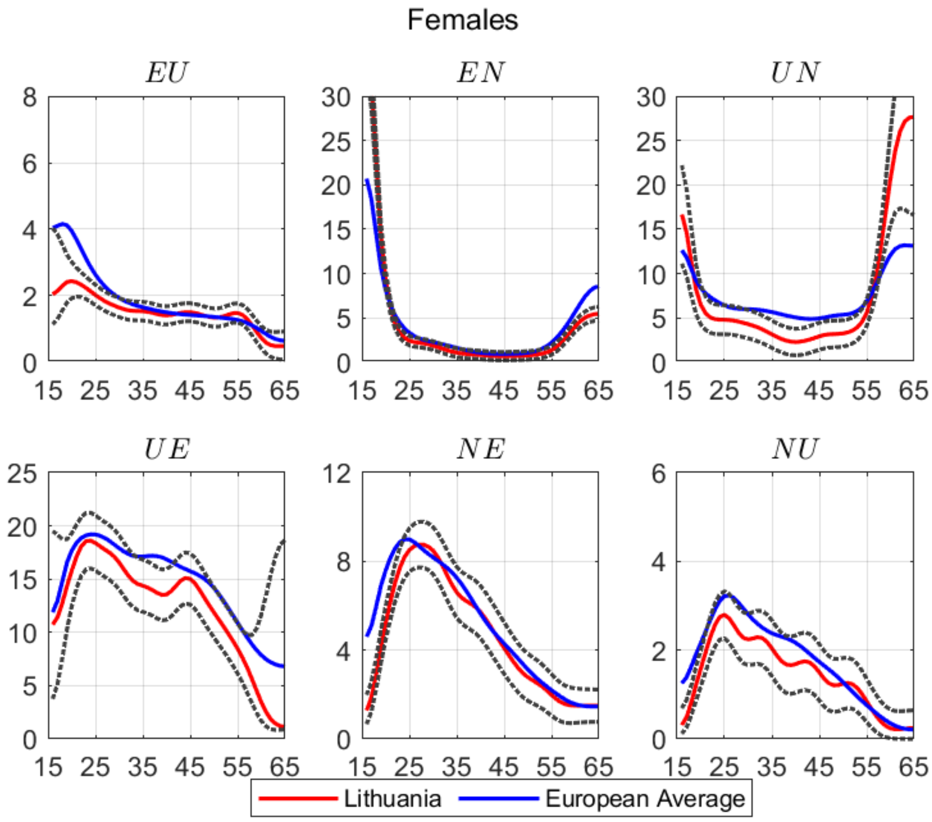
Switching to the life-cycle transition probabilities for women, the picture is less clear. On the one hand, young female workers in Lithuania experience fewer transitions from employment to unemployment (EU), but on the other hand, they are switching to nonparticipation (EN) at a higher rate. Similarly, older women are transiting to nonparticipation at a lower rate when employed (EN) but at a higher rate when unemployed (UN) which works in opposite directions in what concerns aggregate employment. The life-cycle profile of employment in Figure 1 suggests that the latter effect dominates the former.

3.2 Markov Chain

Following much of the literature, we use a first-order Markov chain to link worker stocks and flows data. This process is a key building block of the analysis that we undertake in the next section. It is therefore important to verify whether it can aptly describe the main outcomes of interest.

Starting from the distribution of workers across at age $a = 16$, $\begin{bmatrix} E & U & N \end{bmatrix}'_{16}$, we calculate

Figure 3: Transition probabilities in Lithuania and Europe: Women



Note: Authors' calculation on EU-SILC data. European average is a population-weighted average of all countries in the sample (see in the text).

the predicted stocks in each labor market state at any age $a > 16$, by

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_a = \prod_{\tau=16}^{a-1} \left(\Gamma'_\tau\right)^4 \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{16} . \tag{4}$$

The specific question we address is: based on the quarterly transition probabilities that we estimated in the previous section, are the employment rates implied by a first-order Markov-chain (i.e. based on the stocks in equation (4)) consistent with their actual counterparts? The answer to this question depends not only on the transition probabilities but also on some initial conditions, namely the distribution of workers across E, U, N at age $a = 16$. We set initial conditions by searching a distribution at age 16, $\begin{bmatrix} E & U & N \end{bmatrix}'_{16}$, that maximizes the fit between the Markov-implied employment rates and the actual employment rates.[4]

We obtain a very good fit, which is important, because in what follows we are going to use the statistical model to make a decomposition.

4 Statistical Decompositions

From this point on, for each country we use the initial distribution across E, U, N derived in Subsection 3.2 and the subsequent distributions implied by the Markov chain.

4.1 Framework

Our goal is to relate aggregate cross-country differences in employment rates to the behavior of worker flows over the life cycle. Aggregate differences depend not only on worker flows, but also on demographics and on the initial conditions at age $a = 16$. To see this, denote by E^c the aggregate employment rate of country c, and let E^r refer to some reference employment rate (say, the average of employment rates across the thirty-one countries in our sample). The employment rate of country c is given by

$$E^c = \sum_a W_a^c E_a^c, \tag{5}$$

where W_a^c is the population weight of workers at age a and E_a^c denotes their employment rate.[5] We call E_a^c the age (or life-cycle) profile of employment in country c. To compare c and r, we can use

$$E^c - E^r = \sum_a \left(W_a^c - W_a^r\right) E_a^c + \sum_a \left(E_a^c - E_a^r\right) W_a^r. \tag{6}$$

Equation (6) *minimizes* the role of demographics in explaining employment differences between c and r. Since we have little to say about demographic differences, we seek to keep the demographics-adjusted employment gap, $\sum_a \left(E_a^c - E_a^r\right) W_a^r$, as large as possible.

[4] We use a pattern-search approach to find the initial labor force distribution.

[5] Just like the other life cycle profiles, we extracted W_a^c using the estimation based on equation (2).

Next, consider calculating the life-cycle profile of employment based on country c's transition probabilities and r's initial conditions (instead of using country c's initial conditions). Denote by $\widetilde{E_a^c}$ this counter-factual employment profile. We have:

$$E_a^c - E_a^r = E_a^c - \widetilde{E_a^c} + \widetilde{E_a^c} - E_a^r, \tag{7}$$

which can be plugged into equation (6). So doing, we arrive at

$$E^c - E^r = \underbrace{\sum_a \left(W_a^c - W_a^r\right) E_a^c}_{\text{demographics}} + \underbrace{\sum_a \left(E_a^c - \widetilde{E_a^c}\right) W_a^r}_{\text{initial conditions}} + \underbrace{\sum_a \left(\widetilde{E_a^c} - E_a^r\right) W_a^r}_{\text{transition probabilities}}. \tag{8}$$

In what follows, we focus on explaining the employment gap driven by transition probabilities, namely $\sum_a \left(\widetilde{E_a^c} - E_a^r\right) W_a^r$.

The goal of the subsequent step is to isolate the contribution of each labor market flow to the employment gap due to transition probabilities. Let $\widetilde{E_a^c}^{p_1,p_2,\ldots}$ denote the age-profile of employment in country c starting from r's initial condition *and* using r's transition probabilities $p_1, p_2, \ldots$. The remaining probabilities of the counterfactual transition matrices ($\widetilde{\Gamma}_a$'s) are those measured in country c, and we keep the $\widetilde{\Gamma}_a$'s well defined by adjusting the probabilities of staying in each state $\{EE, UU, NN\}$. So, we decompose the difference in life-cycle employment profiles between c and r due to transition probabilities based on

$$\widetilde{E_a^c} - E_a^r = \underbrace{\widetilde{E_a^c} - \widetilde{E_a^c}^{EU}}_{EU} + \underbrace{\widetilde{E_a^c}^{EU} - \widetilde{E_a^c}^{EU,EN}}_{EN} + \underbrace{\widetilde{E_a^c}^{EU,EN} - \widetilde{E_a^c}^{EU,EN,UE}}_{UE} \tag{9}$$

$$+ \underbrace{\widetilde{E_a^c}^{EU,EN,UE} - \widetilde{E_a^c}^{EU,EN,UE,UN}}_{UN} + \underbrace{\widetilde{E_a^c}^{EU,EN,UE,UN} - \widetilde{E_a^c}^{EU,EN,UE,UN,NE}}_{NE} + \underbrace{\widetilde{E_a^c}^{EU,EN,UE,UN,NE} - E_a^r}_{NU}.$$

Notice that the decomposition of $\widetilde{E_a^c} - E_a^r$ along the lines of equation (9) is path-dependent and thus not unique. In fact, there are $6! = 720$ ways of writing this decomposition, and $2^{6-1} = 32$ ways of measuring the contribution of a given transition probability. The employment rate depends on the transition probabilities in a non-linear fashion, and therefore those different approaches to decomposing $\widetilde{E_a^c} - E_a^r$ might lead to different results. We address this issue using the Shapley decomposition following Shorrocks (2013). The procedure calculates marginal contributions of each transition probability to the aggregate employment gap in all 720 decompositions and then averages them out. The major gain from this approach is that it eliminates path-dependency (i.e. the specific order in which, for instance, we write equation (9)) in the measurement of the role of each worker flow.

4.2 Results

Table 1 presents the results of decomposing Lithuania's aggregate employment gap relative to the population-weighted average aggregate employment in Europe for both genders. All

Table 1: Decomposing the aggregate employment gap: Lithuania vs Europe

	Total gap	Demog-raphics	Initial cond.	Transition probab.	Transition probablities					
					EU	*EN*	*UE*	*UN*	*NE*	*NU*
Males										
PP change	-6.85	-1.3	0.15	-5.7	-2.95	-1.23	-0.35	0.6	-1.5	-0.27
Number of workers (in thousands)	-48.02	-9.13	1.08	-39.96	-20.68	-8.6	-2.48	4.21	-10.51	-1.89
Females										
PP change	1.68	-1.46	-0.1	3.24	0.23	2.29	-0.08	0.4	0.52	-0.12
Number of workers (in thousands)	11.93	-10.38	-0.74	23.05	1.65	16.26	-0.57	2.87	3.67	-0.84

NOTE: Note: Authors' calculation on EU-SILC data. European average is a population-weighted average of all countries in the sample (see in the text). For calculations of the resulting changes in the number of workers, we used the working age population in Lithuania in 2017 (701.4 and 710.5 thousand of men and women, respectively).

effects are expressed in percentage point changes in aggregate employment and in changes of the numbers of employed workers (in thousands). The first column shows the raw aggregate employment gap. In line with Chart 1, the aggregate male employment rate in Lithuania is 6.85 p.p. lower than in Europe, whereas female employment gap is positive at 1.68 p.p. Interestingly, the age composition of population plays an important role in explaining this gap. The effect of demographics is roughly the same for both genders (-1.3 p.p. and -1.46 p.p. for males and females, respectively) and results in a lower level of aggregate employment in Lithuania by almost 20 thousand workers. The recent demographic challenges Lithuania has been facing for the past 15 years (ageing and negative net migration) are the most likely culprits for this result. Lalé and Tarasonis (2019) calculate the same decomposition for all European countries and show that, in the European context, demographic effects are the largest for the Baltic region.

Next, we see that the initial conditions play a negligible role and that labor market dynamics characterized by transition probabilities play by far the largest role in explaining the gap in aggregate employment for both genders.

Focusing on males and looking at the decomposition of each transition rate, the employment exit margin is the main driver of differences, accounting for almost three quarters of the gap in aggregate employment. This is in line with the discussion of Chart 2 above. Specifically, transitions from employment to unemployment (EU) account for almost half of the total effect, whereas probabilities of exiting employment into nonparticipation (EN) are responsible for another quarter. Finally, reentering employment out of nonparticipation (NE) closes the gap, since the contribution of the other two transitions is negligible.

Turning to females, Table 1 shows that most of the observed positive effect of Lithuanian aggregate female employment is due to transitions from employment to nonparticipation (EN). But unlike for men, this has a positive effect on employment. That is, the duration of employment spells is higher for female workers, especially so for young workers. The difference in the life-cycle profile of this transition between males and females in Lithuania is striking, especially given how similar they are in the rest of Europe. Among the remaining transitions, reentering employment out of nonparticipation (NE) plays the largest positive role in explaining higher employment of female workers in Lithuania: relative to others in European countries, they are significantly more likely to come back to employment through this margin.

5 Concluding remarks and policy implications

- Men and women in Lithuania portray similar labor market attachment in terms of their employment rates, both at the aggregate level and throughout the working-life cycle. When compared to the rest of Europe, prime-age men in Lithuania are significantly less employed, whereas women portray larger-than-average employment rates at almost every age.

- We find that employment exit probabilities matter most in explaining large cross-regional differences in aggregate employment. However, its effect is opposite for the two genders. Male employment in Lithuania is low due to larger-than-average probabilities of moving from employment into both unemployment and nonparticipation. Conversely, high employment rates among women is due to the fact that employment spells last longer, as shown by lower-than-average probabilities of transitioning out of employment. It is unclear why the employment exit margin is so different across the two genders, but the policy implications remain the same – it is important to strengthen policies that improve the quality of jobs, sorting between workers and firms so as to increase the duration of employment, or job-to-job mobility of workers between the firms.

- We also find that both male and female older workers in Lithuania suffer from lower-than-average job-finding probabilities and higher-than-average transitions from unemployment to nonparticipation. The main policy implication is that job-seekers need better support, e.g. by boosting resources in the public employment service and increasing participation in training programs. This is especially important for older workers and, unless addressed and alleviated, this effect will likely become even more relevant quantitatively as society continues to age.

- Demographics, namely the composition of age in the working-age population, play an important negative role when comparing aggregate employment rates in Lithuania to the rest of Europe. Demographic challenges, mainly in terms of fast declining population and ageing, need to be addressed in order to alleviate the negative pressure on aggregate employment.

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