DREAM
Danish Research institute for
Economic Analysis and Modelling

MAKRO

Decomposing the Ins and Outs of Unemployment

Cyclical, Structural, and Demographic Trends in the Danish Labor Market

Anders Kronborg and Peter Stephensen

Working paper 2019:1
18 November 2019

www.dreamgruppen.dk

Decomposing the Ins and Outs of Unemployment: Cyclical, Structural, and Demographic Trends in the Danish Labor Market

Anders F. Kronborg* and Peter P. Stephensen, DREAM

November 18, 2019

Abstract

Using highly detailed data on the entire population in Denmark for the period 1980-2015, this paper analyzes labor market flows by decomposing them into three parts: A cyclical, a structural, and a demographic. We do this by explicitely controlling for the business cycle conditions and the net inflow of workers in a set of age-specific dynamic regressions using the Kalman filter. Next, we construct a "bottom-up" unemployment gap which resembles more classical "top-down" used in policy institutions. We find that both job separation and job finding rates are important for explaining aggregate unemployment - the former leading the cycle. Structural unemployment in Denmark has declined significantly since the early 1990's, among other factors likely reflecting major reforms of the labor market. However, our benchmark specification suggests that the drop is 10-15% lower when controlling for favorable demographics during this period. Finally, we use the model to examine the adjustment time to an increase in the labor supply. We find the length of adjustment to have decreased over time with an average of 4-5 years during the sample period.

*E-mail: ank@dreammodel.dk

1 Introduction

Understanding the aggregate unemployment dynamics is key to policy makers and model builders. Often, of particular interest is the decomposition of unemployment into a cyclical (transitory) and a structural (smooth or slow moving) part. Macroeconomic theory has long emphasized a flow approach when modeling the labor market (Mortensen and Pissarides, 1994). Naturally, the empirical labor market literature has given great attention to the cyclical properties of the "ins" and "outs" of unemployment, i.e. the job separation and job finding rates, respectively (see Schimer (2012) for a prominent example). On the other hand, aggregate unemployment exhibits highly persistent variation in many countries which is we might refer to as structural. While this is often attributed to differences in labor market institutions and policies (e.g. Bassanini and Duval, 2006), the aging of population in many economies has sparked a renewed interest in the effects of demographics on labor market outcomes (see Rios and Patutelli (2018) for a recent example).

In this paper, we analyze the labor market flows between employment, unemployment and inactivity, using highly detailed annual register (individual) data on all Danish workers from 1980-2015. Hence, compared to other studies which construct time series from rotating panels from labor force surveys (Blanchard and Diamond, 1990 and Donovan et al., 2018 among many), we are working with the entire population which removes the noise in the data. This allows us to decompose labor market flows by controlling for the business cycle and demographic factors, respectively, in a set of time-varying parameter regressions. After transforming the data, drawing on the approach used in compositional data analysis, these equations are naturally estimated and smoothed using the Kalman filter. This estimation approach further allows us to account for the structural changes in the Danish labor market, not least due to a series of labor market reforms which has reduced the structural unemployment significantly (Andersen and Svarer, 2008). The general aim of this paper is to provide new insights into the relative importance of the three factors as well as how these factors manifest themselves in flows in and out of unemployment.

First, we explore the role of the business cycle on labor market flows. Consistent with other strands of the empirical litterature (for example, see Ghoshray et al., 2016), we allow for age effects by estimating the age-specific labor market flows using a structural component and a measure of the Danish business cycle. By comparing the realized to the estimated structural transition probabilities we construct a "bottom-up" unemployment gap, based on the aggregated age-specific effects. Our model estimate of the aggregate Danish unemployment gap is remarkably similar to the classical "top-down" estimates of leading policy institutions, although it exhibits slightly higher volatility. We then examine the cross-correlation between our measure of the unemployment gap and the job finding and separation rates, respectively. We find the correlation pattern with respect to job separation to be somewhat asymmetrical, implying that it tends to lead the unemployment cycle. On the contrary, job finding exhibits a more symmetrical correlation pattern and moves in conjunction with cyclical unemployment. Finally, when we examine the relative importance of job finding versus job separation rates, we find an approximate 60-40 split in favor of the "ins" (i.e. job separation) during the sample period. This is more pronounced for younger workers whereas the opposite is true for workers close to the retirement age. Except for the oldest age groups, the relative importance of job finding has increased in the later part of the sample period.

Next, we examine the role of demographics. To do so, we construct a set of measures of inflow and outflow to the Danish labor force based on the variation in the age distribution combined with the average historical participation behavior, after controlling for business cycle conditions. Hence, these measures represent exogenous variation in the labor supply purely due to demographic shifts. Two unrelated incidents - large "baby boom" cohorts after the second world war and small cohorts in the early 1980's - implies that the inflow and outflow of workers move rather synchroneously during the sample period, giving rise to substantial fluctuations in the net inflow of workers. Importantly, we find that the model with the business cycle only systematically underestimates (overestimates) the probability of transitioning from employment to unemployment (unemployment to employment) when there is an increase in the labor supply stemming from demographics. These findings are consistent with the presence of a crowding out channel of demographic changes: Larger inflows (lower outflow) of workers amounts to a positive labor supply shock which do not fully translate into higher employment immediately, e.g. due to search and matching frictions. After controlling for the effects of exogenous labor supply on transition probabilities we then assess its contribution to the aggregate unemployment gap. While adverse business cycle conditions were the main cause of the large unemployment gap during the crisis in the early 1990's, our estimates suggest that increasing labor supply contributed as well. On the other hand, decreasing labor supply in the 2000's contributed negatively to the total unemployment gap in this period, including during the financial crisis.

Our findings support the notion that structural changes in the Danish labor market, not least due to an extensive reform agenda, has brought down the structural unemployment rate. Although the majority of the downward trend in aggregate unemployment cannot be explained by favorable demographics, some of it can: In our benchmark specification, the drop in the structural unemployment from its peak in the early 1990's is 10-15% lower when controlling for the inflow and outflow of workers. While this result is qualitatively robust, naturally it depends on the variance restriction used to identify the structural component of labor market transitions. We find that the smooting primarily affects the decomposition - and hence the interpretation - of the early 1990's "hump" in structural unemployment. A less aggressive smoothing implies that this peak is mostly structural as it allows the random walk components to track the realized transitions probabilities more closely. As a result, this leaves less room for cyclical and demographic as explanatory factors and vice versa.

Since we are working with annual data, we cannot observe higher-frequency movements between labor market states within a given year. As Denmark has a relatively flexible labor market with a significant part of the labor force changing job each year, this will lead us to underestimate the magnitude of these flows. However, we find that the cyclical properties of the job finding and separation rates are similar whether we use the gross probabilities or the one-year probabilities, consistent with a continuous time environment as in Schimer (2012). Hence, we conclude that our results are little affected by time aggregation bias, consistent with the findings in Nordmeier (2014).

The first part of this paper is related to a large number of publications, taking a flow perspective to the labor market to assess the decomposition of total unemployment variation. The conclusions about the relative importance of job separation versus job finding rates for cyclical unemployment seems to depend (at least for the US) on the method used to filter out the cyclical component: Schimer (2012) detrends the data using an HP filter with a large degree of smoothing and finds that job finding is strongly procyclical while job separation is almost acyclical. On the other hand, Fujita and Ramey (2009) find support for a separation driven unemployment rate when using a less aggressive smoothing or first-differences of the data as well as controlling for missing observations in the data. Elsby et al. (2013) conduct a similar study on a number of OECD countries and attributes roughly equal importance to job separation and job finding rates for the other two Scandinavian economies (i.e. Norway and Sweden). Perhaps most similar to our approach is Tasci (2012) who uses the Kalman filter to obtain time-varying structural job finding and separation rates. He finds that the stable structural unemployment rate at around 6% reflects offsetting drops in the structural job separation and job finding rates in the US, i.e. generally lower worker reallocation. Our paper differs from these papers in at least two respects: First, we use register data on the entire population instead of survey data. Second, we explicitely control for the business cycle instead of using only statistical filtering and detrending to obtain the cyclical component. The second part of the paper is related to a number of papers which include demography and labor force participation in SVAR models. For example, Wasmer (2009) identifies participation shocks from short-run restrictions and finds that unemployment in major continental European economies are primarily driven by participation, as opposed to the US. Rios and Patutelli (2018) find that the impulse response of unemployment to an aging shock (an increase in the number of people in age groups typically associated with leaving the labor market), while ambiguous in the short run, decreases across German regions after a few periods. Similarly, our findings - at least qualitatively - echoes those in Fuchs and Weyh (2014) and Fuchs (2016) who provide evidence that outflow of older workers contributed to declining unemployment in East Germany, which they refer to as a reversed cohort crowding out effect (the former paper finds this effect to be up to almost

3 p.p. at its peak). Finally, the importance of labor supply shocks for aggregate unemployment is consistent with estimated VAR (Foroni et al., 2018) and DSGE (Smets and Wouters, 2003 and Pedersen and Ravn, 2013) models, respectively. While the mentioned studies focus on the stock of unemployed, we maintain a the flow-based framework, typically used to analyze the labor market through a business cycle lens. Hence, a major contribution of this paper is to merge the two strands of macroeconomic labor market litterature in a single flow-based framework which allows us to study the relative importance of the different factors.

The remainder og the paper is organized as follows. Section 2 presents the flow model of the labor market as well as the data set used in the analysis. Section 3 investigates the cyclical properties of labor market transitions, in particular job finding and job destruction. We construct a measure of exogenous labor supply and assess its effects in Section 4. In Section 5 we check the robustness of our results. Section 6 concludes.

2 A flow model of the labor market

2.1 Data

To study the labor market flows we use the Danish administrative register data which consists of highly detailed individual information on the entire population from age 15 to 68. The data set has annual observations from 1980 to 2015 and includes information on the primary labor market status in the last week of November, the yearly labor income and various benefit schemes (for example unemployment benefits, student grants, early retirement benefits, and state pension), private pension income as well as whether the individual is currently under education. Since we observe all individuals over time, we can observe directly their flows between different labor market states at discrete time periods.

The definition of unemployment differs somewhat from the standard definition in the literature, mainly due to its historical use for administrative purposes: An individual is defined as unemployed if she meets one of two conditions: i) Not being employed in the reference week *and* receive unemployment benefits (“dagpenge”). ii) Not being employed *and* receive cash benefit (“kontanthjælp”) *and* classified as job-market-ready (“group 1”) by the job center.[1] As the database gives priority to recorded employment in the reference week, we apply the following definitions used in the analysis below: If an individual is under education she is classified as a student (outside the labor force) even if she is employed. If an individual has received public pensions (either state or early retire-

[1]This differs, for example, from the Current Population Survey (CPS) in the US where an individual is unemployed if "[...] *they do not have a job, have actively looked for work in the prior 4 weeks, and are currently available for work.*", where actively looking is defined from certain activities, see https://www.bls.gov/cps/.

ment) for more than DKK 10,000 in a given year, she is classified as retired (outside the labor force) even if she is employed.

2.2 Describing labor market flows

We examine the flow of workers between three labor market states: Employment (E), unemployment (U) and inactive/outside the labor force (I). The labor market conditions can then be summarized by the following matrix of transition probabilities:

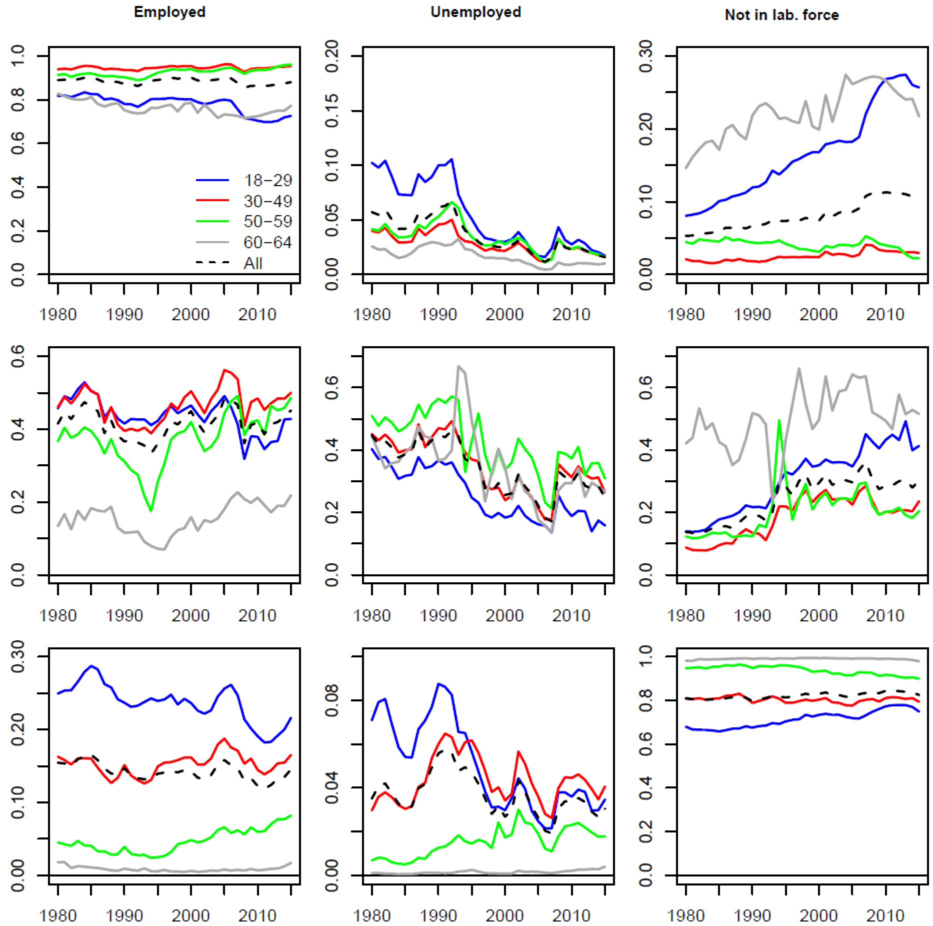
$$P_{a,t} = \begin{pmatrix} p_{a,t}^{E,E} & p_{a,t}^{E,U} & p_{a,t}^{E,I} \\ p_{a,t}^{U,E} & p_{a,t}^{U,U} & p_{a,t}^{U,I} \\ p_{a,t}^{I,E} & p_{a,t}^{I,U} & p_{a,t}^{I,I} \end{pmatrix}. \tag{1}$$

Hence, $p_{a,t}^{i,j}$ denotes the probability that a worker with age a transitions from state i in period t to state j in period $t+1$ and the matrix in (1) can be computed as the realized share of workers between periods during the sample period. In the sections below, we decompose the labor market flows to account for the effects of the business cycle, structural changes, and exogenous movement in the labor supply stemming from demographic changes.[2] Our approach thus assumes that individuals at a given age are homogeneous and that Markov assumption holds.

Figure 1 depicts the matrix in (1) in the sample period, aggregated for different age groups. Several features of the data are worth highlighting here: First, several entries exhibit clear time trends, likely reflecting structural changes in the Danish labor market, including a large number of reforms during the 1990's and 00's or the general education level in the population (Bækgaard and Helsø, 2018). For example, all age-groups were much more likely to stay in an unemployed state ($p_{a,t}^{U,U}$ in $P_{a,t}$) in the beginning of the sample than in the end, even counting the years during the financial crisis. The probability of transitioning from the employed state to the unemployed ($p_{a,t}^{E,U}$) similarly shows a persistent declining pattern, which is of course consistent with the decline in Danish headline unemployment in the sample period. Second, transition probabilities varies considerably in the age-dimension. Retirement and the choice to begin an education means that the oldest and the youngest age groups are much more likely to flow from employment or unemployment to inactivity than any other age group. The "backbone" of the labor market, people aged 30-49 years, are more likely to stay in employment than any other age group in (almost) the entire sample period. Third, the flows show clear sign of the Danish business cycle. For example, the transition probability of going from employment to unemployment has local maxima during the

[2]Besides the obvious advantage, that flow data allows a more granular analysis of unemployment, Barnichon and Nekarda (2012) shows that forecasting the flows of workers and adding them up to the stock of unemployed improves the forecast performance.

Figure 1: Realized transition probabilities, by age group.



Note: Based on gross flows from 1980-2015. The probabilities are calculated as the average of the realized transitions of all individuals.

adverse macroeconomic conditions in the early-mid 1990's, in the brief 2001 recession and following the financial crisis in 2008-2009.

Since we are working with yearly data we run the risk of significant aggregation bias. Therefore, when we refer to the job separation and job finding rates below, they have been computed as the one-year transition probabilities consistent with a continuous time environment from a set of differential equations in the spirit of Schimer (2012). However, in Section 5 we show that time aggregation is not likely to affect our results in general.

Before any estimation is done, we transform the transition probabilities using logit scaling as in Stephensen (2016). I.e. we assume that the elements in (1) are given by

$$p_{a,t}^{i,j} = \frac{exp\{\alpha_{a,t}^{i,j}\}}{\sum_s exp\{\alpha_{a,t}^{i,s}\}}. \tag{2}$$

Such transformations are often used in compositional data analysis to be able to use standard, unconstrained econometrics on a constrained, nonlinear problem (for example, see Kynclova and Filzmoser, 2015). In the present application, (2) maps the transformed data from the three-dimensional real space to the Aitchison simplex for each row in (1) and all age groups. In Section 5, we consider an alternative transformation frequently used in the compositional data analysis literature but find that this has minor implications for our results.

3 The effects of the business cycle

The analysis in this section is based on a decomposition of the labor market transition probabilities into a cyclical and a structural component. In order to disentangle structural developments in the Danish labor market from those pertaining to transitory shocks, we use the Kalman filter to estimate the following set of state space models for each set of states, (i, j) and each age group, a (we drop the superscripts below for notational simplicity):

$$\begin{aligned} \alpha_{a,t} &= \phi_{a,t} + \beta_a Y_t + \varepsilon_{a,t}, \quad \varepsilon_{a,t} \sim N(0, \sigma^2_{a,\alpha}) \\ \phi_{a,t} &= \phi_{a,t-1} + \eta_{a,t}, \quad \eta_{a,t} \sim N(0, \sigma^2_{a,\eta}) \end{aligned} \tag{3}$$

where $\alpha_{a,t}$ follows from (2) and Y_t is some business cycle measure which in part reflects the aggregate demand for labor. We use the output gap of the Danish Ministry of Finance in our benchmark specification. The effects of the business cycle on labor market flows are allowed to be age-dependent. This is consistent with multiple empirical studies that find for example that young people were more adversely affected by the financial crisis (European Commission, 2010) and that unemployment of young people has a business cycle sensitivity in general (Ghoshray et al., 2016). Finally, Benati (2001) finds that discouraged worker effects are more pronounced for older workers, relatively close to retirement. The structural level of the transition probability from state i to state j is captured through the unobservable component $\phi_{a,t}$ which we allow to be age-dependent as well, consistent with the data (see Figure 1). We think of this as a structural component, reflecting a range of different long-term changes in labor market institutions, education, preferences, etc. To obtain this decomposition we identify the structural component by a variance restriction, i.e. we think of "structural" as a smooth process. Specifically, we impose the restriction that $\sigma^2_{a,\alpha} = \lambda\sigma^2_{a,\eta}$, with a benchmark ratio of 20 which visually gives the desired smooth development in structural probabilities. Further, this degree of smothing implies that a 5% unemployment gap (defined below) is approximately as moderate as 1/5% change in the structural unemployment level at quarterly frequency, as recommended by EU Independent Fiscal Institutions in their "Practitioner's Guide" (Network of EU IFIs, 2018). We examine the robustness of this parametrization is investigated in Section 5.

Once we have obtained the decomposition of the transition probabilities we can construct a time series of the unemployment gap, i.e. the deviation of aggregate unemployment from its structural level due to business cycle fluctuations. Let the initial state at time t be given as $n_{a,t} = (E_{a,t}, U_{a,t}, I_{a,t})'$, where $E_{a,t}$ denotes the number of workers with age a employed at time t, etc. The unemployment gap is then given as:

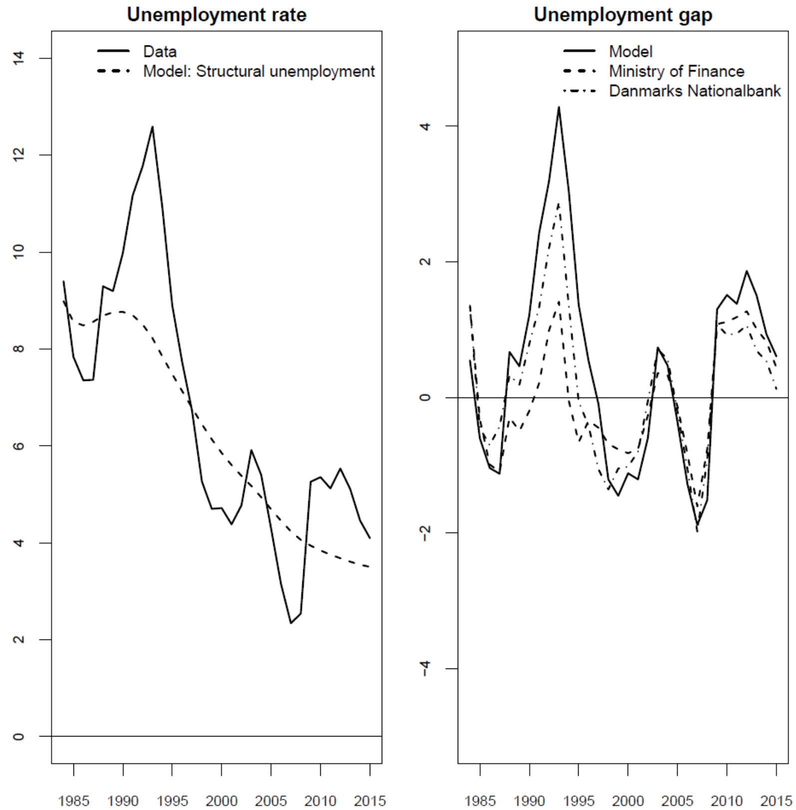
$$\hat{u}_{t+1} \equiv u_{t+1} - u_{t+1}^{struc} = \frac{\sum_a \left(U_{a,t+1} - U_{a,t+1}^{struc}\right)}{E_{t+1} + U_{t+1}} = \sum_s \left(p_{a,t}^{s,U} n_{a,t}^s - p_{a,t}^{struc,s,U} n_{a,t}^s\right), \quad s = \{E, U, I\}, \quad (4)$$

where

$$p_{a,t}^{struc,i,j} = \frac{exp\{\phi_{a,t}^{i,j}\}}{\sum_s exp\{\phi_{a,t}^{i,s}\}},$$

$E_t \equiv \sum_a E_{a,t}$, and $U_t \equiv \sum_a U_{a,t}$. We might call the measure in (4) - with a partitioning of the Markov matrix in an actual and structural (or potential) component - a "bottom up" unemployment gap since probabilities are used to add up to the aggregate stock of unemployed workers for a given initial condition. This can be compared to the "top-down" approach usually applied by domestic and international policy institutions, where the unemployment gap is typically estimated from an aggregate production and a Phillips curve directly on aggregate time series (see for example Danielsen et al., 2017 and Havik et al., 2014). Figure 2 shows our model's decomposition of the aggregate unemployment (left graph) as well as the unemployment gap from (4) (right graph). The structural unemployment rate is clearly decreasing from around 9 in the early 1990's to less than 4% in the final sample year. The model's unemployment gap is compared to the classical "top-down" gap from the Ministry of Finance and Danmarks Nationalbank (the Danish central bank). Although there are some differences, our model estimate of the unemployment gap is remarkably similar to the two policy institutions, both in magnitude and with respect to the timing of peaks and troughs. We assess the crisis in the early 1990's to be worse, especially when comparing with the Ministry of Finance estimate - with a peak gap of 4.3 versus 1.4 p.p. - although it is closer to the central bank estimate of 2.6 p.p. Further, our unemployment gap closed more slowly compared to both alternatives. In later years, the measures generally track each other closely, even if we estimate the adverse labor market conditions after the crisis to be slightly worse than both policy institutions with a peak gap of 1.9 p.p. versus 1.2 p.p. on average. Overall, we conclude that our model is able to separate the cyclical variation from the structural trends in aggregate unemployment, even though it is estimated from a flow perspective.

Figure 2: A bottom-up unemployment gap



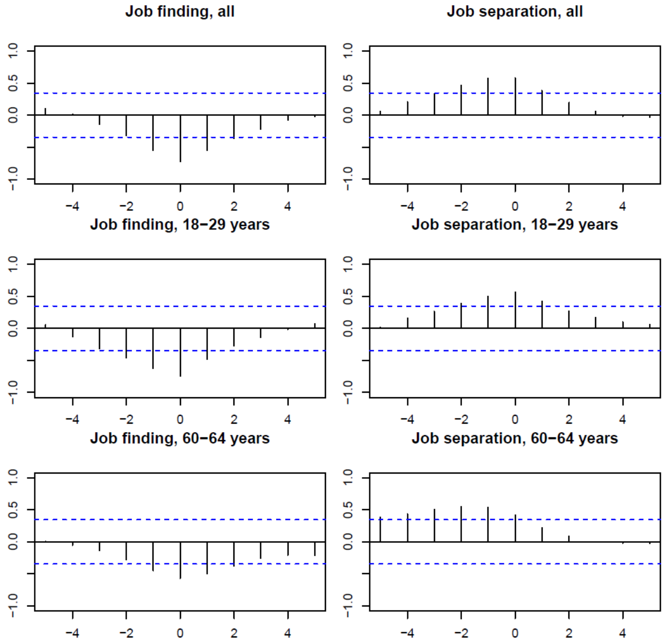
Note: Based on gross flows from 1985-2015. The structural unemployment level and the resulting gap is calculated as shown in (4).

Next we examine the cross correlation between our unemployment gap in (4) and the job finding and job separation rates, respectively. In the text below we follow most of the literature and define JF_t and JS_t respectively, as the one-year probability of job finding and job separation rates consistent with a continuous time environment, assuming only transitions between E and U. Hence, these measures should in principle not be affected by potential time aggregation bias, compared to the gross transition probabilities in (1). The results are shown in Figure 3. The unemployment gap has a positive and significant correlation with the job separation rate, especially at impact and for negative lags, meaning job separation generally moves ahead the unemployment gap. For the job finding rate, this correlation is noticeably more symmetrical with negative and significant correlations at almost similar magnitudes for both at leads and lags. The results suggest that job separation primarily moves ahead of or early in the business (unemployment) cycle, while the job finding rate affects it symmetrically during the cycle.[3]

Finally, we look at the cyclical contribution of the job finding and job separations rates, re-

[3]A similar conclusion is reached in Fujita and Ramey (2009) on US data, although they look at HP-filtered unemployment and in first differences instead of a gap measure.

Figure 3: Cross correlation between the unemployment gap and the job finding/separation rate



Note: Computed based on (continuous time) hazard rates. The unemployment gap is computed as shown in (4).

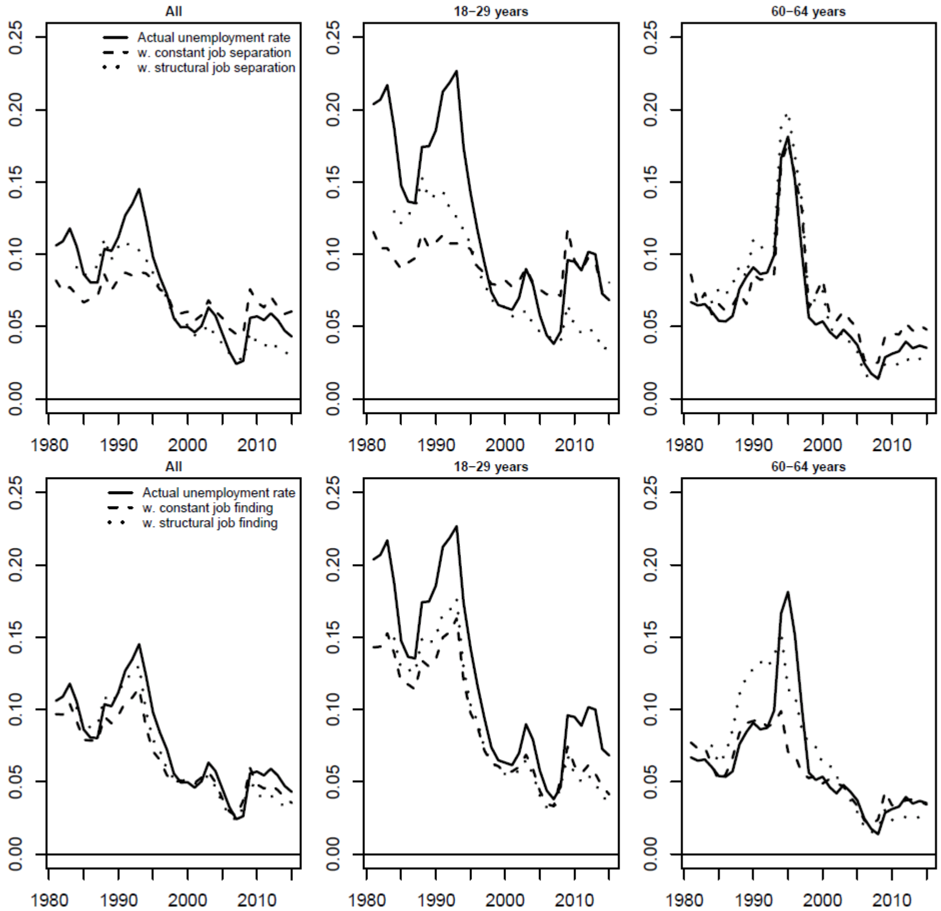
spectively, by considering the aggregate unemployment rate in several counterfactual scenarios. As noted in Schimer (2012), the unemployment rate in period $t+1$ can be approximated by $JS_t/\left(JS_t + JF_t\right)$ in the short run. Their relative importance for the unemployment cycle can then be assessed, either by fixing it to the sample average or setting it to its structural level, cf. (3). The results are shown in Figure 4. The graphs illustrate that variations in the job finding rate are cyclical but do not explain the majority of unemployment fluctuations during the sample period, although the correlation seems stronger in the second half of the sample. Further, a constant job separation is a better assumption for older workes than younger.

Next, we quantify the relative cyclical importance from the following approximation of the unemployment gap:

$$\hat{u}_t \equiv u_t - u_t^{struc} \approx \frac{JS_t}{JS_t + JF_t} - \frac{JS_t^{struc}}{JS_t^{struc} + JF_t^{struc}}. \tag{5}$$

Table 1 reports the "betas" of the regressions where JS_t and JF_t are set to their structural levels, respectively. E.g. $\beta^{JS} = cov(\hat{u}_t, \frac{JS_t^{struc}}{JS_t^{struc}+JF_t} - \frac{JS_t^{struc}}{JS_t^{struc}+JF_t^{struc}})/var(\hat{u}_t)$ and similarly for β^{JF} (note that since (5) only holds approximately these coefficients do not sum to 1). Over the entire sample and for the working force as a whole, we find an approximate 60-40 split in favor of the "ins" (i.e. job separation) when is comes to explaining the unemployment gap. This is more pronounced for younger workers whereas the opposite is true for workers close to the retirement age. Except

Figure 4: Counterfactual job finding and separation rates: Contributions to aggregate unemployment



Note: Computed based on (continuous time) hazard rates. Top row is $\bar{JS}_{A,t}/\left(\bar{JS}_{A,t}+JF_{A,t}\right)$ and bottom row is $JS_{a,t}/\left(JS_{a,t}+\bar{JF}_{a,t}\right)$, where A denotes the relevant age group and a "bar", means that the rate is set to either the sample mean or the structural level.

for the oldest age groups, the relative importance of job finding has increased in the later part of the sample period.

That job separation (the "ins of unemployment") is the cyclically most important factor, at least in the early parts of a boom or recession, is in accordance with several empirical studies on US data (Blanchard and Diamond, 1990 and Fujita and Ramey, 2009). Further, this result is consistent with widely used macroeconomic models of the labor markets. For example, in the model in Mortensen and Pissarides (1994) with endogenous job finding and separation, the latter is shown to be the most volatile in face of aggregate demand shocks. However, we are able to confirm the findings in Elsby et al. (2013) that this is much less pronounced for the Nordic countries, where the relative importance is closer to equal.

Table 1: Importance of job finding and job separation rates for the unemployment gap. Computed based on (continuous time) hazard rates.

	Full sample (1983-2015)		
	All	18-29 years	60-64 years
Structural job separation	0.37	0.28	0.71
Structural job finding	0.60	0.69	0.21
	First half		
	All	18-29 years	60-64 years
Structural job separation	0.33	0.25	0.73
Structural job finding	0.63	0.73	0.18
	Second half		
	All	18-29 years	60-64 years
Structural job separation	0.46	0.36	0.63
Structural job finding	0.54	0.60	0.45

Note: The unemployment gap is defined in (4).

4 The effects of demographics

The model in Section 3 provides information on labor market outcomes resulting from the business cycle. However, it does not say anything about the effects of labor supply, even if these are empirically acknowledged to play an important role. In the presence of matching frictions, labor supply shocks might significantly affect the aggregate unemployment rate at business cycle frequencies (see for example Blanchard and Diamond, 1989 and Foroni et al., 2018). This section expands the analysis above by introducing exogenous variation in the labor supply due to demographic changes.

4.1 Constructing a measure of exogenous labor supply

To begin our examination we construct a measure of the aggregate labor supply pertaining to the exogenous demographic variation in the size of age groups typically associated with the inflow and outflow of workers to the economy. To do so we need to decide at what age we count people as entering and leaving the labor market, respectively. Instead of defining the thresholds at some arbitrary values, say 25 and 60 years, we want to let the data decide. We do this by constructing a set of kernels: One for inflow of new workers, $K_I(a)$, and one for outflow of existing workers, $K_O(a)$, from the workforce. The kernels are based on the average change in the labor force participation rate at each age during the sample period and scaled to unity. In this way, most weight will be put on age groups that were historically most likely to enter or leave the labor market. Instead of taking the raw participation rate we use the structural changes in the participation rates as obtained from (3). We find that controlling for business cycle effects in this way significantly reduces the noise and extracts a clear pattern in the age-dependent participation rates. Finally, we truncate each kernel by considering $A_I = [21; 30]$ and $A_O = [57; 66]$. After we obtain the historical participation behaviour with respect to inflow and outflow we average and scale it to unity.

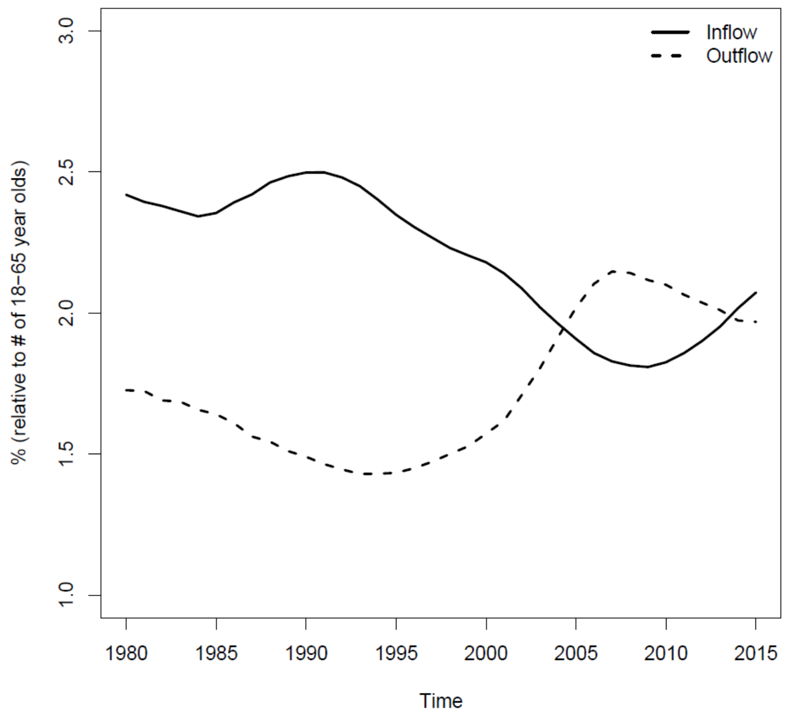
Once we have obtained our kernels we can construct the inflow (I_t) and outflow (O_t) as follows:

$$\begin{aligned} I_t &= \frac{\sum_a K_y(a) N_{a,t}}{\sum_a N_{a,t}}, \\ O_t &= \frac{\sum_a K_o(a) N_{a,t}}{\sum_a N_{a,t}}, \end{aligned} \tag{6}$$

where $N_{a,t}$ is the number of people at a given age a at time t and $K_I(a) = 0$ for $a \notin A_I$ and $K_O(a) = 0$ for $a \notin A_O$. $\sum_a K_I(a) = \sum_a K_O(a) = 1$. By keeping the weights constant during the sample period we avoid capturing the effects of labor market reforms (e.g. raising the age at which people are eligible for the publicly funded state pension) in I_t and O_t. Hence, such structural change will still be captured by the term $\phi_{a,t}$ in equation (3) while our measures of labor supply will capture the average effects of demography of the transition probabilities. We scale the weighted number of people in age groups A_I and A_O by the total size of the workforce at time t to obtain a measure of the *relative* size of the labor supply shock. Figure 5 shows our synthetic measure of inflow and outflow from the labor market computed from (6). It is worth noting that the inflow and outflow of workers have moved inversely for a large part of the sample period. Increasing labor supply stemming from the inflow of new workers peaks at around 1990 and then decreases until around the time of the financial crisis after which it increases. Similarly the decreasing labor supply stemming from outflow troughs in the early mid 1990's and peaks around or just prior to the financial crisis and then declines again. These gross flows both have a negative *net* effect on labor supply from around mid 1990's until the financial crisis, after which they both have a net positive effect.

We would like to note that this coinciding increase in inflow and decrease in outflow and vice versa during the sample period is generally not found previous to 1980 nor in Danish population forecasts (Hansen and Stephensen, 2012). It is instead the result of two unrelated demographic incidents: The first is the presence of very large cohorts in the years following the Second World War, also found in many other countries. This accounts for the peak in O_t from the mid 00's and afterwards. The peak in I_t at around 1990 "echoes" this as it roughly corresponds to the children of the post-war cohorts. The decline in I_t until the financial crisis is the result of low fertility in particular during the early 1980's resulting in a series of small cohorts. We use this natural experiment in the estimation below.

Figure 5: Measures of inflow and outflow of the Danish labor force



Note: The inflow and outflow measures are defined in (6). The weights for each age-group is based on the average structural transitions probabilities, computed from (3).

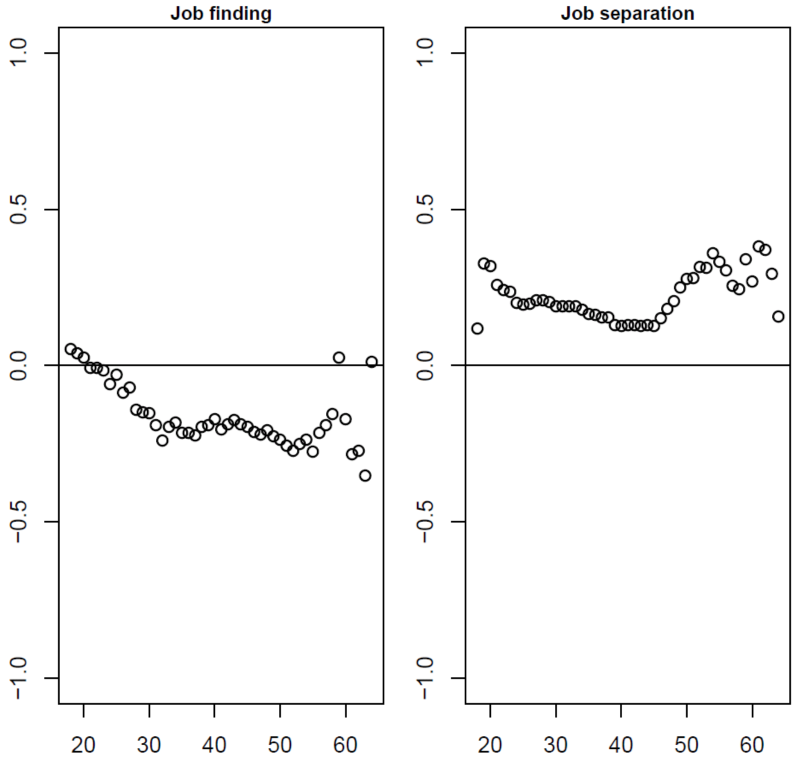
4.2 Estimation

If labor market flows were only affected by a structural and a business cycle component we would expect the series of $\varepsilon_{a,t}$ in (3) to be resembling white noise, or at least have no correlation with our constructed measures of labor supply. As figure 6 shows, this turns out not to be the case. For example, the residuals in the job separation equation are positively correlated with the net inflow of workers from both measures for all age groups. Or put in another way: We systematically underestimate the probability of transitioning from employment to unemployment when the aggregate labor supply increases (and vice versa), even after we control for business cycle conditions. The age groups most affected by inflows and outflows are, perhaps not surprising, the youngest and the oldest workers, whereas workers in their late 30's and 40's seem to be affected the least. Similarly, the model with a cyclical and structural component only systematically overestimates the job finding rate in periods with increasing labor supply.

We quantify the effects by estimating the following set of equations:

$$\hat{e}^{i,j}_{a,t} = \delta_a + \delta^I_a K_{I,t} + \delta^O_a K_{O,t} + \eta^{i,j}_{a,t}, \tag{7}$$

Figure 6: Correlation between supply measures and residuals in transition probabilities by age



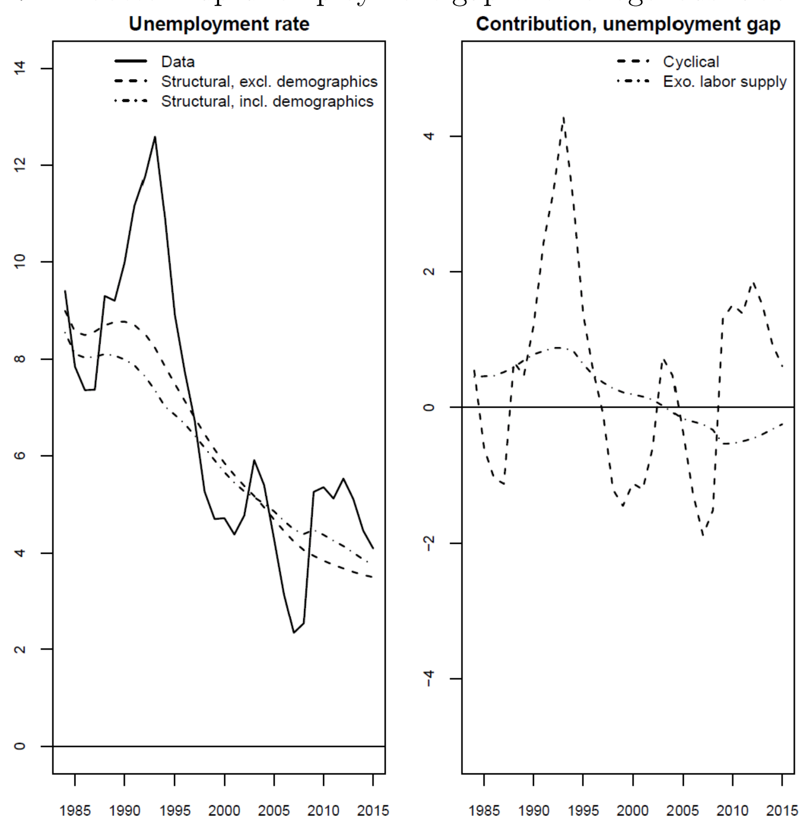
Note: Computed based on (continuous time) hazard rates. The residuals are obtained from the business cycle only-model in (3).

where $\hat{\varepsilon}^{i,j}_{a,t}$ is the estimated residuals from (3), ie. $\hat{\varepsilon}^{i,j}_{a,t} = \alpha^{i,j}_{a,t} - \phi^{i,j}_{a,t} - \hat{\beta}_a Y_t$. As before we allow the effects to be age dependent consistent with recent studies that emphasize the importance of this dimension in determining the aggregate unemployment rate (e.g. Barnichon and Mesters, 2018 and Hornstein and Kudlyak, 2019). One can think of (7) as correcting the model for systematic effects of our labor supply measures.[4] The advantage of this approach is that we get to keep our (reasonable) estimate of the structural probabilities from Section 3. Hence, this avoids any contaigion from persistent variation in inflows and outflows to the structural level, which we identified by a smoothness restriction.

Figure 7 shows the unemployment gap in (7) when we correct for exogenous variation in the aggregate labor supply. The left graph depicts the structural unemployment rate from before as well as the new "super structural" rate, where we have controlled for both cyclical and demographic factors. This measure of structural unemployment is still clearly decreasing but less steeply than the original measure. The reason is that peak structural unemployment - and shortly hereafter peak actual unemployment - coincides with the peak of net inflow into the labor force making

[4]This does not imply that (3) suffers from omitted variable bias, since $K_{I,t}$ and $K_{O,t}$ are based on demographic fluctuations which will be unaffected by any business cycle measure, Y_t.

Figure 7: A bottom-up unemployment gap with exogenous labor supply



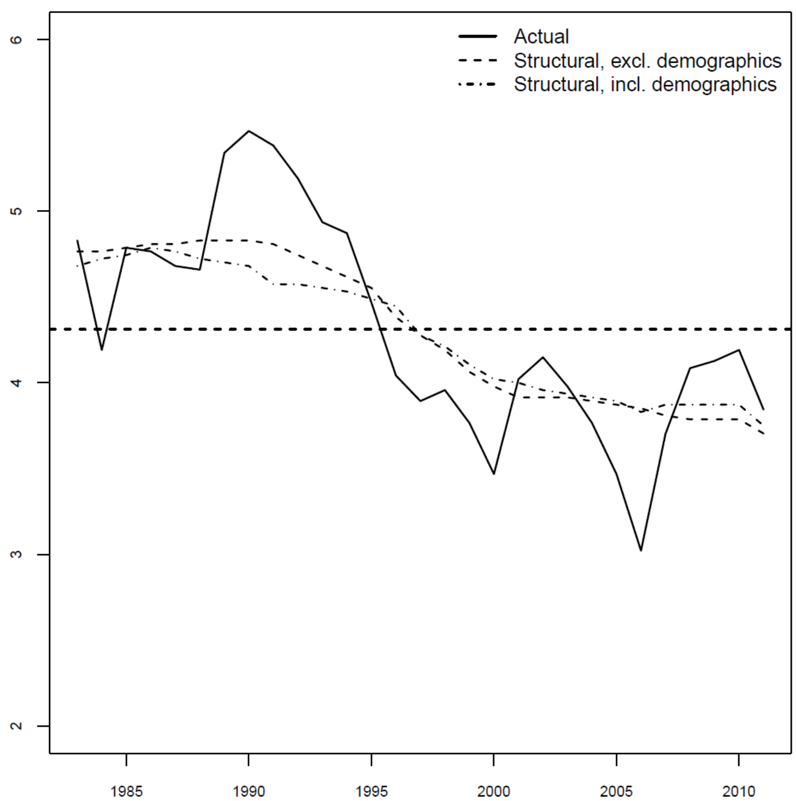
Note: Based on gross flows from 1985-2015. The structural unemployment level excluding demographics and the resulting gap is calculated as shown in (4). The structural level including demographics has been adjusted as shown in (7).

it harder to find a job and less likely to stay in one than under neutral labor supply conditions. Hence, while adverse business cycle conditions were still the main cause of the large unemployment rate in 1993, net inflow of workers contributed as well. Our results suggest that adverse cyclical conditions can account for approximately 4.3 p.p. (or approximately 83%) of the total ("total" here is *both* demand and exogenous labor supply) unemployment gap in 1993 versus 0.9 p.p. (or 17%) which was caused by an increase in the exogenous labor supply. On the contrary, the new measure of structural unemployment has been higher in recent years, including prior to the financial crisis, compared to the pure cyclical model, due to gradually lower net inflow of workers up until the trough in 2008. Hence, our estimates suggest that negative supply of labor reduced the unemployment gap approximately 0.5 p.p. when the crisis hit (compared to a cyclical-driven gap of +1.5 p.p.). In this respect, one might argue that the crisis in the early 1990's (often ascribed to contractive domestic fiscal policy and the currency crises at the time, see for example Abildgren, 2010) was ill-timed, whereas the financial crisis (largely a global phenomenon) is an example of a well-timed crisis.

4.3 Adjustment to an increase in the labor supply

In Denmark it has been lively discussed how fast the speed of adjustment to labor supply shocks is, i.e. how fast does the demand side absorb increases in the labor supply? Our model provides a natural framework to answer this question. Since aggregate labor market flows can be calculated based on an initial condition and the matrix of transition probabilities in (1) we can fairly easily construct a counterfactual path were a number of unemployed workers, say 100 people, are added initially as unemployed. The adjustment speed is then calculated as the number of years it takes for most of these workers to exit unemployment. As our convergence criteria, we say that a labor supply shock is converged when the impulse response (counterfactual unemployment relative to the benchmark) changes by less than 2% of the original shock size. This is obviously somewhat arbitrary but a fairly strict convergence criteria and so the adjustment time reported below might be seen as conservative estimates. Figure 8 shows the average adjustment time over all age groups for each year during the sample period. To gauge the effects of demand and supply conditions, respectively, we plot the adjustment time for both the actual (ex post) and the two measures of structural transition probabilities from Section 3 and 4. Based on Figure 8 we conclude the following: The average adjustment time has varied somewhat during the sample period, between 3 and 5.5 years with a sample (time) average of $4-5$ years. It mirrors the business cycle conditions in the sense that large degrees of labor market slack is associated with longer adjustment times and vice versa. The speed of adjustment is higher in the second part of the sample, which might be due to institutional changes in the Danish labor market. As mentioned earlier, a series of reforms were implemented starting in the early 1990's among other things to reduce long-term unemployment. The drop in adjustment time should be seen in light of a more flexible labor market and healthier incentives (Andersen and Svarer, 2008). The adjustment time for the two structural measures relative to the actual adjustment time indicates the span of influence that favorable or adverse cyclical and demographic conditions have. Our results suggest that business cycle conditions have affected the adjustment to labor market reforms from $+0.5$ to -0.8 years during the sample, i.e. the business cycle affects the adjustment time with a year and a half from peak to trough. Exogenous variations in the labor supply are estimated to account for much less, between $+0.2$ to -0.1 years. The latter suggests that the adjustment time should be fairly constant with respect to the size of labor market reforms or, put in another way, the effects of labor market shocks are fairly linear. Even during the first half of the 1990's where our meassures indicates that the labor force may have grown by 1% per year the counterfactual adjustment time was mainly elevated due to business cycle conditions.

Figure 8: Average adjustment time (years) to labor supply shocks



Note: The figure shows the time of convergence when 100 people of a given age are counterfactually added to the workforce, initially as unemployed. The figure shows the average across the age-groups from 18-64 years. The structural adjustment times are based on (3) and (7), respectively. Convergence is defined as an absolute decrease in the "impulse response" function of less than 2.5%.

5 Robustness

We now proceed to investigate the robustness of our results. First, we check whether our results are robust to the transformation used in (2). We re-estimate our model using instead the isometric logratio transformation (ilr) proposed by Egozcue et al. (2003). In the present application, the ilr is the linear mapping between the Aichison simplex and $\mathbb{R}^2$ which preserves all metric properties (an isometric linear mapping). This has very little effects on our results: For example, the structural unemployment rate according to the model is identical up to the third decimal point (as a result, we do not report these numbers). Thus, we conclude that our results are not dependent on the particular transformation used. Also, we considered a specification with 5 states as in Ward-Warmedinger and Macchiarelli (2013), adding "students" and "retired" to the inactive labor market state but found that this had little effect on our results.

Working with annual frequency as in our data set runs the risk of time-aggregation bias. Since we do not observe higher-frequency movements between labor market states within a given year we certainly underestimate the magnitudes of flows (hence before interpreting the job finding and job separation rates in Section 3 we corrected for this). However, this would only be problematic for us if the cyclical properties of the continuous time one-year probabilities were different from the gross probabilities that we use in our estimations. Figure 9 depicts both the gross one-year probability of job finding and job separation, respectively, as well as the corresponding one-year probability consistent with a continuous time environment. Visually, there seems to be little cyclical bias introduced from the frequency of the data. This is confirmed by the descriptive statistics in Table 2. The continuous time one-year probabilities are only marginally more weakly correlated with business cycl, which mean that our estimates are likely to be rather unaffected by the data frequency. This finding is in contrast to those in Schimer (2012) where job separation in the US become acyclical after correcting for time aggregation, but is similar to Nordmeier (2014) who finds that time aggregation bias is quantitatively unimportant in Germany (albeit she considers quarterly data).

Table 2: Descriptive statistics: Gross vs. continuous time one-year probabilities

	Job finding		Job separation	
	Gross	Continuous	Gross	Continuous
Sample average	0.42	0.43	0.04	0.06
Standard dev. (gap)	0.03	0.03	0.01	0.01
Correlation with business cycle (gap)	0.85	0.83	-0.79	-0.77

Note: The continuous time one-year probabilities are computed from a two-state model and scaled back to the three-state case.

Since the decomposition of cyclical and structural transition probabilities depend on the vari-

Figure 9: Gross vs. continuous time one-year probabilities

Note: The continuous time one-year probabilities are computed from a two-state model and scaled back to the three-state case.

ance restriction λ we check the robustness of our main conclusion by varying this parameter. First, it is worth noting that our benchmark value of 20 leads to an appropriate degree of smoothing at the aggregate unemployment level (the variance ratio is close to 39 as recommended in Network of EU IFIs (2018)), as shown in Table 3. Since a less aggressive smoothing allows the random walk component of the filter to track the realized transition probabilities more closely, we would expect a lower λ to leave less room for cyclical and demographic factors.

Figure 10 generally confirms this, i.e. both the cyclically and demographically induced gaps exhibit higher volatility when the structural transition probabilities are more smooth. Interestingly though, the cyclical unemployment gap is mainly affected in the first half of the sample, due to the severe crisis in the early 1990's. For the later periods, this implies that our model's ability to identify the cyclical component of agrgegate unemployment through the transition probabilities is robust to the degree of smoothing. Hence, λ mainly determines the decomposition of the non-cyclical labor market flows into a demographic and "super structural" component. As seen from

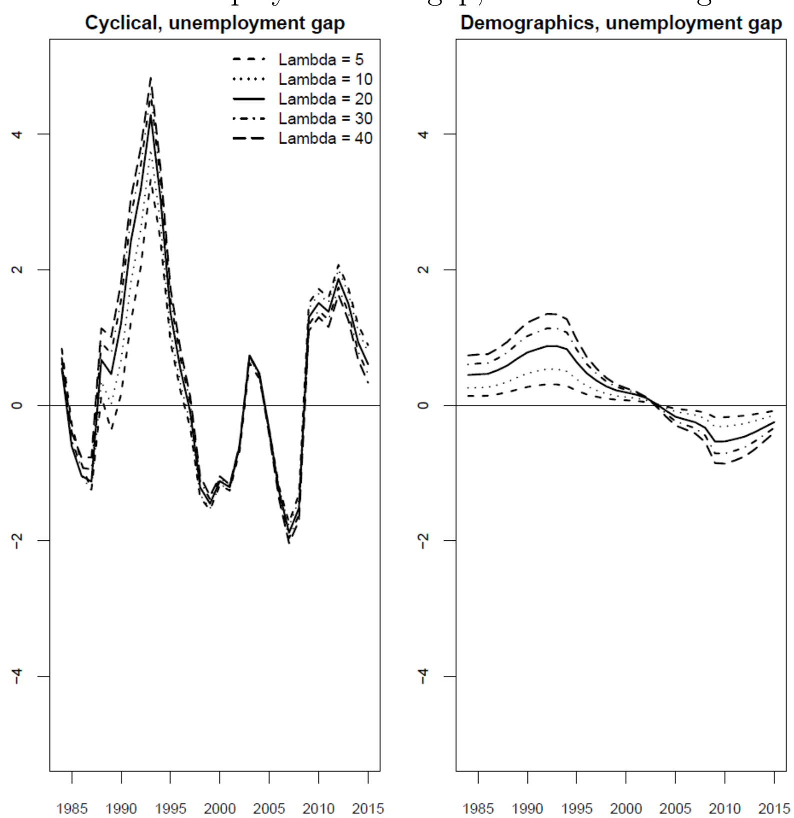
Table 3: Resulting ratio of variances of shocks to structural vs. cyclical unemployment for different smoothing values, λ

λ	5	10	20	30	40
$\frac{\sigma_g^2}{\sigma_{struc}^2}$	8	15	32	48	59

Note: σ_g^2 is the variance of the innovations of the buttom up unemployment gap, found by fitting an ARMA-process to the series. σ_{struc}^2 is the variance of the structural unemployment rate and is found as $var(\Delta u_t^{struc})$ defined as in (4). As noted in Network of EU IFIs (2018) *a variance ratio of ≈ 39 implies a good level of smoothing at annual frequency.*

Figure 10 (right graph), a higher λ uniformly "flattens" the unemployment gap due to demographics but does not affect the general shape, nor the sign of the effect. Thus, we conclude that our results with regard to the effects of exogenous labor supply are qualitatively robust.

Figure 10: Structural unemployment and gap, for different degrees of smoothing



Note: Based on gross flows from 1985-2015. The figure shows the cyclical and demographic effects on the total unemployment gap for different levels of smoothing. The structural level includes demographics, i.e. it has been adjusted as shown in (7).

6 Conclusions

Using highly detailed data on the entire population in Denmark for the period 1980-2015, this paper analyzes labor market flows by decomposing labor market flows into three parts: A cyclical, a structural, and a demographic. We do this by explicitely controlling for the business cycle conditions as well as the net inflow of workers to the labor force in a set of age-specific dynamic regressions. This allows us to quantify the relative importance these factors from a flow perspective.

We construct a "bottom-up" unemployment gap using our model estimates and show that this resembles the more classical "top-down" approaches used in policy institutions. We find that job separation leads the unemployment cycle, whereas the job finding rate moves more symmetrically with the cycle. The results suggest that both the "ins" and the "outs" of unemployment are cyclically important with an approximate 60-40 split. Looking more detailed at the age-dimension, we find that variations in the job finding rate is relatively more important for older compared to younger workers. The importance of the job finding rate has increased in the second part of the sample.

To examine the role of exogenous labor supply, we construct a set of measures of inflow and outflow to the Danish labor force, respectively. Based on the historical participation behavior, we can subsequently control for the effects of demographics on labor market flows. The estimates suggest the presence of a cohort crowding out effect: We find that, while structural factors and adverse cyclical conditions were the main causes of high unemployment in the early 1990's, demographics contributed with around 0.9 p.p. (or 22% of the total unemployment gap) at the peak of the crisis. On the other hand, decreasing labor supply in the 2000's meant that unemployment was 0.4 p.p. lower when the financial crisis hit than what would have been the case under neutral labor supply conditions. Hence, in terms of variations in the total labor supply relative to the business cycle, we find that the crisis in the early 1990's was ill-timed, whereas the recent financial crisis is an example of a well-timed crisis.

Finally, our model provides a natural framework to examine the speed of adjustment to labor market shocks: Since we can add a number of unemployed workers to the initial state, we can construct counterfactual labor market flows and compare to the baseline scenario. Based on a fairly conservative convergence criteria we find the adjustment time to be around 4-5 years but declining during the sample, possibly reflecting a more flexible labor market. Our results suggest that business cycle conditions can affect the adjustment by around 1 year, compared to the case of neutral business cycle conditions.

Appendix

A Additional graphs

Figure 11: Coefficients of the output gap on the transformed transition probabilities

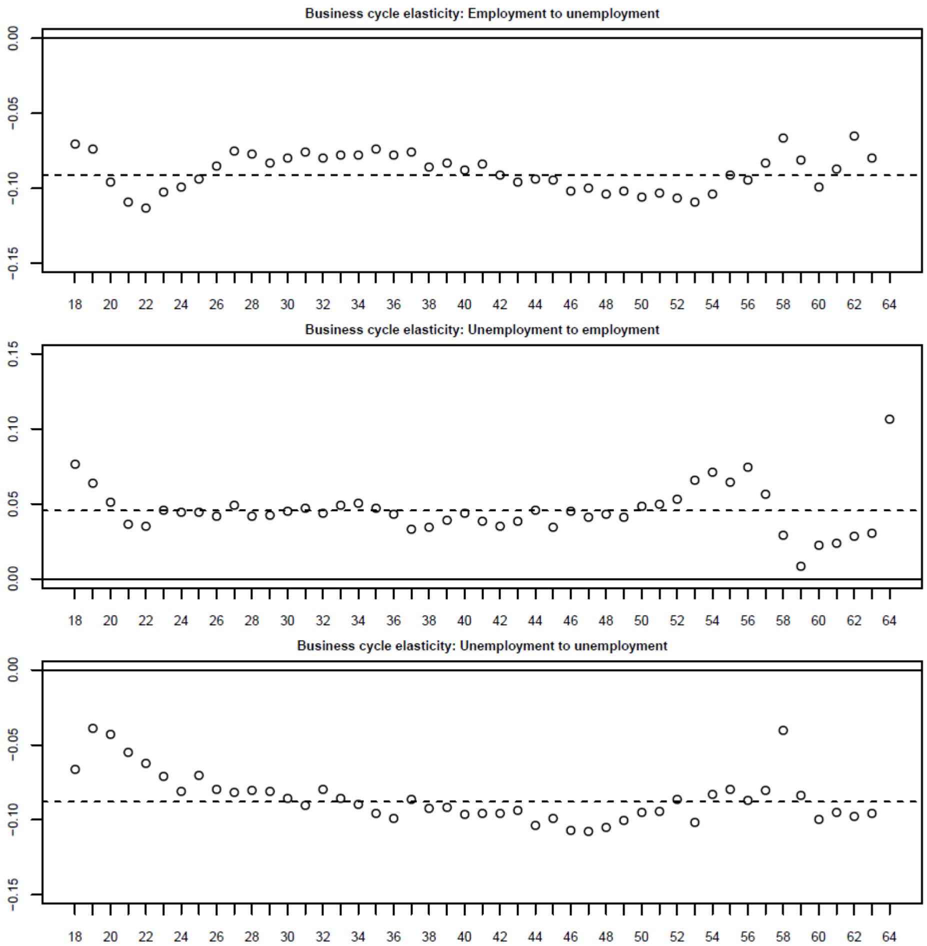
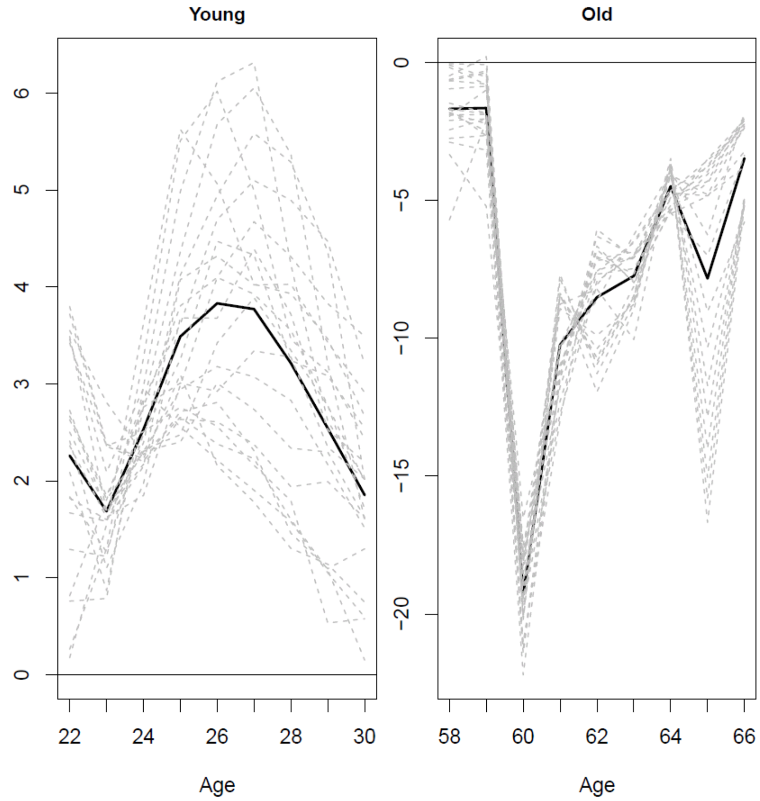


Figure 12: Change in structural participation rate by age



Note: The structural participation rate is calculated as a counterfactual flow of workers using the decompotition in (3). The solid line is the average over each year in the sample (grey dashed lines).

References

Abildgren, K. (2010). *Dansk Pengehistorie 1990-2005.* Danmarks Nationalbank.

Andersen, T. M. and Svarer, M. (2008). Flexicurity in denmark. *ifo DICE Report.*

Bækgaard, H. and Helsø, A. K. (2018). The danish labour force 1980-2015 - and the importance of education. *DREAM Working Paper.*

Barnichon, R. and Mesters, G. (2018). On the demographic adjustment of unemployment. *Review of Economics and Statistics.*

Barnichon, R. and Nekarda, C. J. (2012). The ins and outs of forecasting unemployment: Using labor force flows to forecast the labor market. *Brookings Papers on Economic Activity.*

Bassanini, A. and Duval, R. (2006). Employment patterns in oecd countries: Reassessing the role of policies and institutions. *OECD Working Papers.*

Benati, L. (2001). Some empirical evidence on the 'discouraged worker' effect. *Economic Letters.*

Blanchard, O. and Diamond, P. (1989). The beveridge curve. *Brookings Papers on Economic Activity.*

Blanchard, O. and Diamond, P. (1990). The cyclical behavior of the gross flows of u.s. workers. *Brookings Papers on Economic Activity.*

Danielsen, T. K., rgensen, C. W. N. J., and Jensen, R. M. (2017). Revisiting potential output in denmark. *Danmarks Nationalbank working papers.*

Donovan, K., Lu, J., and Schoellman, T. (2018). Labor market flows and development. *Society for Economic Dynamics.*

Egozcue, J. J., Meteu i Figueras, G., Pawlowsky-Glahn, V., and Vidal, C. B. (2003). Isometric logratio transformations for compositional data analysis. *Mathematical Geology.*

Elsby, M. W. L., Hobijn, B., and Sahin, A. (2013). Unemployment dynamics in the oecd. *The Review of Economics and Statistics.*

European Commission (2010). Employment in europe 2010. *European Commission Manuscript.*

Foroni, C., Furlanetto, F., and Lepetit, A. (2018). Labor supply factors and economic fluctuations. *International Economic Review.*

Fuchs, M. (2016). Unemployment decline in east germany: the role of demography. *Review of Regional Research.*

Fuchs, M. and Weyh, A. (2014). Demography and unemployment in east germany. *IAB-Discussion Paper.*

Fujita, S. and Ramey, G. (2009). The cyclicality of separation and job finding rates. *International Economic Review.*

Ghoshray, A., Ordonez, J., and Sala, H. (2016). Euro, crisis and unemployment: Youth patterns, youth policies? *Economic Modelling.*

Hansen, M. F. and Stephensen, P. (2012). Danmarks fremtidige befolkning: Befolkningsfremskrivning 2012. *DREAM Forecast Series.*

Havik, K., Mc Morrow, K., Orlandi, F., Planas, C., Raciborski, R., Roeger, W., Rossi, A., Thum-Thysen, A., and Vandermeulen, V. (2014). The production function methodology for calculating potential growth rates & output gaps. *European Commission Economic Papers.*

Hornstein, A. and Kudlyak, M. (2019). Aggregate labor force participation and unemployment and demographic trends. *Federal Reserve Bank og San Frasico Working Paper series.*

Kynclova, P. and Filzmoser, O. (2015). Modeling compositional time series with vector autoregresive models. *Journal of Forecasting.*

Mortensen, D. T. and Pissarides, C. A. (1994). Job creation and job destruction in the theory of unemployment. *The Review of Economic Studies.*

Network of EU IFIs (2018). A practitioner's guide to potential output and the output gap. *Available at:.*

Nordmeier, D. (2014). Worker flows in germany: Inspecting the time aggregation bias. *Labour Economics.*

Pedersen, J. and Ravn, S. H. (2013). What drives the business cycle in a small open economy? evidence from an estimated dsge model of the danish economy. *Danmarks Nationalbank Working Papers.*

Rios, V. and Patutelli, R. (2018). *What is the effect of Population Ageing in Regional Labour Market Fluctuations of Germany? A SVAR with Zero-Sign Restrictions Approach.* Springer.

Schimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics.*

Smets, F. and Wouters, R. (2003). An estimated dynamic stochastic general equilibrium model of the euro area. *Journal of the European Economic Association.*

Stephensen, P. (2016). Logit scaling: A general method for alignment in microsimulation models. *International Journal of Microsimulation.*

Tasci, M. (2012). The ins and outs of unemployment in the long run: Unemployment flows and the natural rate. *Federal Reserve Bank of Cleveland Working Paper.*

Ward-Warmedinger, M. and Macchiarelli, C. (2013). Transitions in labour market status in the european union. *LEQS - LSE 'Europe in Question' Discussion Paper Series.*

Wasmer, E. (2009). Links between labor supply and unemployment: theory and empirics. *Journal of Population Economics.*