Aggregate Labor Force Participation and Unemployment and Demographic Trends*

Andreas Hornstein — FRB Richmond
Marianna Kudlyak — FRB San Francisco

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Abstract

We estimate trends in the labor force participation and unemployment rates of demographic groups differentiated by age, gender, and education, using a parsimonious statistical model of age, cohort and cycle effects. We find that the estimated trend in the aggregate unemployment rate declined monotonically from 7% in 1976 to 4.5% in 2017, and that this decline is almost exclusively driven by demographic factors, about equal contributions from an older and more educated population. The estimated trend of the aggregate LFP rate is hump shaped with a peak in 2000 and is currently at 63%. The LFP trend is not only driven by demographics, with increasing educational attainment being important throughout the sample and ageing of the population becoming more important since 2000, but also by changes of groups' trend LFP rates, e.g. for women prior to 2000. Extrapolating the estimated trends using CBO population forecasts we project that over the next 10 years the trend LFP rate will decline to 60.5% and the trend unemployment rate will decline to 4.8%.

Keywords: Labor Force Participation Rate. Unemployment Rate. Demographic Composition. Age Effects. Cohort Effects.

*Any opinions expressed are those of the authors and do not reflect those of the Federal Reserve Bank of Richmond, the Federal Reserve Bank of San Francisco or the Federal Reserve System. E-mail addresses: andreas.hornstein@rich.frb.org, marianna.kudlyak@sf.frb.org.

1 Introduction

Researchers and policymakers are very interested in decomposing the unemployment rate and the labor force participation (LFP) rate into their long-run trends and more transitory cyclical components. Deviations of these rates from their long run trends serve as a signal of the labor market's health. Most of this discussion proceeds at an aggregate level, but unemployment and LFP rates differ systematically across demographic groups defined by age, gender and education (so called socio-demographic factors).[1] Unemployment rates tend to be lower for older and more educated workers, labor force participation rates tend to be lower for older and less educated workers, and historically men tend to have lower unemployment rates and higher LFP rates than women. The aggregate unemployment and LFP rates are functions of population-share weighted sums of the demographic groups' rates. Similarly, the trend in the aggregate rates depends on the weighted sum of the trends of the groups' rates. Given the differences in the rates across demographic groups, changes in demographic composition of the population change the aggregate trend rate, even if the trend rates of the demographic groups remain unchanged.

In this article, we estimate trends for the LFP and unemployment rates of demographic groups defined by age, gender and education, and we use these trends, together with the groups' population shares, to construct the trends of the aggregate LFP and unemployment rate. We estimate the groups' trends using a parsimonious statistical model of age, cohort, and cycle effects, and we define the trend as the sum of the age and cohort effects. The estimated trend in the aggregate unemployment rate declined almost monotonically from 7% in 1976 to 4.5% in 2017, and the cyclical deviations of unemployment from its trend are substantial. The decline in the trend unemployment rate is almost exclusively driven by demographic factors, about equal contributions from an older and more educated population. The estimated trend in the aggregate LFP rate is hump shaped with a peak in 2000, and cyclical deviations from its trend tend to be small. The trend LFP rate is not only driven by demographics, with increasing educational attainment being important throughout the sample and ageing of the population becoming more important since 2000, but also by changes of groups' trend LFP rates, e.g. for women prior to 2000.

Our approach, building up the trend of the aggregate LFP rate from trend estimates of group-specific age-cohort models, is not new. The existing literature has used age-cohort models of the demographic groups' supplemented by a large number of additional controls, e.g. Aaronson, Cajner, Fallick, Galbis-Reig, Smith, and Wascher (2014).[2] Typically, the

[1] See our illustrative example in Section 2 below.

[2] Related papers using the age-cohort model are Aaronson, Fallick, Figura, Pingle, and Wascher (2006),and

time variation of the age-specific rate of a demographic group is attributed to cohort effects and the age effect is taken as fixed. But age-specific rates vary quite a bit more than can be accounted for by cohort effects. For example, older workers participate at higher rates in the labor market now than two decades ago; young workers, 16-24 years old, participate at a much lower rate than in the 1990s. Augmenting the model with additional controls such as school enrollment, social security payouts and others helps capture the evolving age effects. Our alternative approach is to allow for time variation in age effects, while being explicit about the stochastic processes that drive age and cohort effects, in particular, we assume a random walk structure. The resulting model can be estimated using standard Kalman-filter techniques.

Another paper closely related to our work is Barnichon and Mesters (2018) who estimate the trend unemployment rate. They emphasize that the aggregate unemployment rate is jointly determined by the trends in group unemployment and LFP rates, and that changes in a demographic group's trend unemployment rate are likely related to changes in its trend LFP rate. For this reason Barnichon and Mesters (2018) estimate a dynamic factor model for labor force status transition rates which jointly determine LFP and unemployment rates. For demographic groups defined by age and gender they argue that accounting for the joint determination of unemployment and LFP trends significantly affects the estimated trend for the aggregate unemployment rate. We will argue that, despite some notable changes for groups' trend LFP rates, changes in population shares play a larger role for the aggregate unemployment rate trend once one also takes into account demographic trends in educational attainment.

The rest of the paper is structured as follows. Section 2 illustrates the systematic differences of unemployment and LFP rates for a coarse decomposition of the U.S. population. Section 3 describes the estimation framework, including notes on the data. Section 4 describes the results for the estimates of cycle and trend of the unemployment rate and LFP rate across demographic groups. Section 5 describes the results for the trend of the aggregate LFP rate and unemployment rate. Section 6 concludes.

Montes (2018). Additional empirical investigations of the trend LFP rate are conducted in Hotchkiss, Pitts, and Rios-Avila (2012), Diamond (2013), Elsby, Hobijn and Sahin (2013), Fallick and Pingle (2007), Balleer, Gomez-Salvador and Turunen (2009), Kudlyak (2013), Erceg and Levin (2013).

2 Demographics of the labor market, 1979 and 2017

Before we provide a formal analysis of the differences in labor market outcomes across demographic groups and how they change over time, Table 1 illustrates these differences for a coarse decomposition of the U.S. population aged 25 and older. We use the micro CPS data to calculate annual averages of unemployment and LFP rates, and population shares. We split the population by age, less than 55 years old versus 55 years and older, gender, men versus women, and education, high school or less versus some college or more. Data are available for the years 1976 to 2017. In order to see how group rates have changed over time absent business cycle effects, we calculate the rates and population shares for the two years with an aggregate unemployment rate trough at the beginning and end of the sample, 1979 and 2017.

Panel (A) illustrates that the unemployment rate is lower for more educated workers and that it tends to be lower for older workers. Over time it appears that the unemployment rate has increased for men and for older women, but changes have been small, less than one percentage point for any of the demographic groups. Panel (B) illustrates that the LFP rate is lower for less educated workers, for older workers, and for women. Over time the LFP rate has decreased for men and increased for women, independent of education and age, and changes have been noticeable, between 5 and 10 percentage points.

Finally, from Panel (C) we can see that over time the U.S. population has gotten older, the share of those older than 55 years increased by about 7 percentage points, and more educated, the share of those with more than a high school education increased by about 30 percentage points. Holding group unemployment rates and LFP rates fixed, the shift towards an older and more educated population lowers the aggregate unemployment rate. For the LFP rate these same two demographic shifts have opposing effects. In what follows we will construct trend measures of the demographic groups' unemployment and LFP rates and then attribute changes in the aggregate trends to changes in trend group rates and demographic shifts.

3 Framework for trend estimates

In this section, we describe our simple model of trend and cycle for demographic groups. Suppose we have observations on the outcome q (labor force participation rate or unemployment rate) and the population share p of demographic group i at time t for age groups a or cohorts $t-a$

$$\begin{aligned} Q_i &= \{q_{a,i,t} : t = 1, \ldots, T \text{ and } a = 1, \ldots A\} \\ P_i &= \{p_{a,i,t} : t = 1, \ldots, T \text{ and } a = 1, \ldots A\}. \end{aligned}$$

For a particular demographic group we write the observed outcome for its age groups as a linear function of unobserved cohort effects, x, age effects, y, and cycle/time effects, z,

$$q_{a,i,t} = x_{a,i,t} + y_{a,i,t} + z_{a,i,t} + \varepsilon^q_{a,i,t} \text{ with } \varepsilon^q_{a,i,t} \sim N\left(0, \sigma^2_{a,i,q}\right), \tag{1}$$

with $\varepsilon^q_{a,i,t}$ iid. We assume stochastic processes for age, cohort, and cycle effects that are independent across demographic groups and will drop the group index when no confusion can arise. In particular, we assume that the age and cohort effects follow random walks

$$\begin{aligned} x_{1,t} &= x_{1,t-1} + \varepsilon^x_{1t} \text{ with } \varepsilon^x_{1t} \sim N\left(0, \sigma^2_{1x}\right) \\ x_{a,t} &= x_{a-1,t-1} \text{ for } a > 1 \\ y_{a,t} &= y_{a,t-1} + \varepsilon^y_{a,t} \text{ with } \varepsilon^y_{a,t} \sim N\left(0, \sigma^2_{ay}\right) \text{ for } a \geq 1, \end{aligned}$$

where $\left\{\varepsilon^x_{1t}, \varepsilon^y_{a,t}\right\}$ are i.i.d. The initial cohort effect of a new cohort is a random variation of the initial effect of the new cohort in the previous period. We assume that the cohort effect remains fixed over the life time of a cohort, that is, cohort effects are fixed birth-year cohort effects. There is a common cyclical effect to all age groups of a demographic group and we assume that it either follows an AR(1) process

$$z_t = \rho z_{t-1} + \varepsilon^z_t \text{ with } \varepsilon^z_t \sim N\left(0, \sigma^2_z\right) \text{ and } \|\rho\| < 1$$

with ε^z_t iid, or it is observed. If the cyclical effect follows an AR(1) process its impact on an age group is

$$z_{a,t} = \gamma_a z_t.$$

The coefficients γ capture systematic age-related differences in the response to the common cyclical component z, and we normalize the impact on the first age group, $\gamma_1 \equiv 1$.[3] If the cyclical effect is observed, we assume its impact on an age group is a moving average of its current value and one lag and lead

$$z_{a,t} = \sum_{s=-1}^{+1} \gamma_{a,s} z_{t-s}.$$

[3] Alternatively, we could have normalized the variance of the innovation to the common cyclical component, $\sigma^2_{z.}$

and there is no need to normalize γ. We define the trend of a group's outcome as the sum of the age and cohort effects,

$$q^T_{a,t} = x_{a,t} + y_{a,t}.$$

We apply out model to annual averages of observable outcomes and population shares, and we aggregate our cohorts into age groups 16-19, 20-24, 25-34, etc. Thus the observation equations for age groups are

$$\bar{q}_{g,t} = \frac{1}{\#A_g} \sum_{a \in A_g} x_{a,t} + \bar{y}_{g,t} + \bar{z}_{g,t} + \bar{\varepsilon}^q_{g,t}.$$

The transition equations for annual cohort effects remain as they are but the transition equations for the age and cycle effects now apply to time-averaged age groups, not individual age groups.[4]

We use maximum likelihood to estimate the parameters $\Theta = \left\{\sigma_{\bar{q},g}, \sigma_x, \sigma_{\bar{y}}, \sigma_{\bar{z}}, \rho, \gamma_g\right\}$ if the cycle component is not observed, and the parameters $\Theta = \left\{\sigma_{\bar{q},g}, \sigma_x, \sigma_{\bar{y}}, \gamma_{g,s}\right\}$ if we observe the cycle component. We estimate the unobserved state (age, cohort, and cycle) using the Kalman filter conditional on parameters Θ. For each demographic group defined by gender and education our estimation proceeds in two steps. First, we estimate the model for the group's unemployment rate assuming that the cycle effect z^u_t is not observed. Second, we estimate the model for the group's labor force participation rate, taking the group's inferred cyclical indicator for its unemployment rate as observed. We use this procedure since labor force participation rates are highly persistent and estimating the cyclical indicator directly yields highly persistent processes.[5]

Given the random walk nature of our cohort and age group effects we define the trend of a group as the sum of the estimated age and cohort effects

$$\bar{q}^T_{g,i,t} = \frac{1}{\#A_{g,i}} \sum_{a \in A_{g,i}} x_{a,i,t} + \bar{y}_{g,i,t}.$$

We use the smoothed posteriors for our estimates of the age and cohort effects. The trend of the aggregate LFP rate is then the population share weighted sum of the groups' trend LFP rates

$$l_t = \sum_{g,i} p_{g,i,t} l^T_{g,i,t}, \tag{2}$$

[4] We will apply our model to the levels of unemployment and LFP rates. Alternatively, we could apply the model to the log levels of the rates, which would mean that the calculate geometric averages for the age groups.

[5] Alternatively, we could have used the demographic group's observed unemployment rate as the cyclical indicator for the group's LFP rate.

and the trend of the aggregate unemployment rate is

$$u_t = \frac{\sum_{g,i} p_{g,i,t} l^T_{g,i,t} u^T_{g,i,t}}{\sum_{g,i} p_{g,i,t} l^T_{g,i,t}} \tag{3}$$

For this purpose, we treat the population shares of different groups as exogenous.[6]

3.1 Data and empirical implementation

The data in the analysis are constructed from the monthly basic files of the Current Population Survey (CPS) from January 1976 to December 2017. We use the CPS labor status variable to classify each member of the civilian non-institutionalized population of age 16 or older as employed, unemployed or out of the labor force. We aggregate the individual micro data into age-gender-education cells using the CPS-provided sampling weights. Finally, for each cell we construct the unemployment rate, the LFP rate and population shares.

The age groups are 16-19, 20-24, 25-34, 35-44, 45-54, 55-64, and 65 years and older. The educational categories for those aged 25 and older are less than high school, high school, some college, and college or higher. Note that we do not differentiate the young, those aged 24 or less, by education. Consequently, we have 44 age-gender-education cells.

We estimate our state-space model separately for young men and women, not differentiated by education, and for each gender and education group for individuals aged 25 and older. To forecast the trend, we need a forecast of the population shares and a forecast of the trend unemployment and LFP rates. We use our estimates of the trend to construct groups' trend forecasts. We use CBO population forecasts to construct population shares by age and gender (CBO, 2018). We then estimate a cohort-age model of educational attainment to construct a forecast of the age-gender shares by education. The details of that estimation are in Appendix A.

4 Demographics of unemployment and LFP

We now apply our framework to the unemployment rates and LFP rates of the demographic groups defined bye age, gender, and education and and characterize their trend and cycle. Group unemployment rates move together over the cycle, the least (most) educated group is the most (least) volatile, and volatility declines with age. Group LFP rates are not very cyclical, except for those 16-19 years old whose LFP rate is strongly pro-cylical, and the oldest college educated group whose LFP rate is strongly counter-cyclical.

[6]For the purpose of calculating LFP rate and unemployment rate projections we later relax this assumption somewhat with respect to education.

Removing the cyclical components we find not much of a change in the trend values of the group unemployment rates. To the extent that group unemployment trends change there is no uniform pattern to the contributions of age and cohort effects. Turning to group LFP rates we find large and systematic changes in their trends: for those younger than 25 years LFP rates declined for men and women alike, and for those 25 years and older the LFP rates of men declined and the LFP rates of women increased. Again, age and cohort effects contribute about equally to these changes, with cohort effects being somewhat more prevalent among women. While error bounds for estimates of group trend LFP rates are quite narrow, trend unemployment rates are subject to large degree of uncertainty.

4.1 Unemployment rates: cycle and trend

The common cyclical components of the different demographic groups' unemployment rates move together and therefore with the aggregate unemployment rate. Figure 1 displays the common cycle effects by education for men (top panel) and women (bottom panel). With respect to education, the least educated group (less than high school) is the most cyclically volatile and the most educated group (college or higher) is the least cyclically volatile group. The cyclical volatilities of the other two education groups and those less than 25 years old are bracketed by these two groups. This characterization applies to both men and women, with the womens' cycle effects being somewhat less volatile. Finally, comparing across recession episodes, we find that for all groups the cyclical unemployment factor reached a higher level during the 2007-09 recession than in all other recessions. This is most noticeable for the highest educated group which has never moved much over the cycle except for the 2007-09 recession.

With respect to age, older groups are less cyclically sensitive than younger groups for all education levels. Table 2 displays the estimated age-coefficients on the common cyclical factor by education for men (top panel) and women (bottom panel). For all groups the coefficient on the cyclical factor declines gradually with age, independent of gender and education. For less educated men and women (less than high school) there is also a pronounced step down for those aged 65 years and older.

We identify the trend unemployment rate of a group with the sum of that group's age and cohort effects. With few exceptions we do not find large changes in group trends from the 1980s to the present. The changes we do observe are mostly less than one percentage point. The exceptions are the most educated prime age women whose trend unemployment rate declines by about 2 percentage points, and the least educated younger (older) males whose trend unemployment rate decreases (increases) by a bit more than 1 percentage point.

Across the different groups, age and cohort effects both contribute to trend changes with no apparent systematic pattern, except for the least and most educated prime age women where cohort effects seem to dominate.

In Table 3 we report changes in the groups' trend unemployment rates from 1979 to 2017. This exercise replicates the exercise from the introduction, Table 1, with a finer demographic grid and a more systematic removal of cyclical effects. The results from the two exercises are broadly consistent.

For men we find more increases than decreases in the trend unemployment rate across age and education groups. Most of the changes are small, less than one percentage point, except for the least educated males. For these individuals with less than a high school education the trend rate declines for those between 25 and 44 years old, but increases for those 55 and older. Overall, age effects seem to account for more of the trend changes, but there is no clear pattern.

For women we find the opposite than for men. There are more age-education cells where the trend unemployment rate declines, but again for most groups the changes are small, except for the most educated prime age women. For women aged 25 to 55 years with a college education the trend unemployment rate declined by 1 to 2.5 percentage points. Also, unlike for men, cohort effects seem to account for more of the trend changes across women's age-education groups. This is especially true for the most educated prime age women and for women aged less than 25 years which we do not differentiate by education.

We illustrate the role of cohort and age effects in Figure 2 for the group of men with less than a high school education. The top five lines plot the age effects for our five age groups, and the bottom line marked with circles plots the cohort effects for those entering the sample at age 24, starting in 1960.[7] Clearly, age effects are not constant over time. There are short-run movements in the age effects such as the increase for 25-34 year old men during the 1980s recession, and there are medium-run swings such as the decline and then increase of the age effect for men 65 and older. The short-run swings in age effects suggest that our estimation method does not always extract the cycle for all demographic groups.[8] The medium-run swings reflect, in part, changes in the relative trends of different age groups. Finally, there are also notable medium-run swings in cohort effects, but movements in the

[7] We estimate age effects for the duration of our sample starting in 1976, and we can infer cohort effects for those entering the sample prior to 1976.

[8] We are hesitant to interpret the apparent cyclical responses in age effects as persistent scarring of that particular age group. Scarring would be better reflected in a change to the cohort effect, but our estimation imposes a fixed cohort effect.

cohort effects tend to be small relative to movements in age effects.[9][10] The estimates of the age and cohort effects are not very precise. The dashed lines in Figure 2 represent two standard error bands based on the smoothed posterior variances of the unobserved states. Note that the changes of age and cohort effects over time usually stay within their initial error bands. These wide error bands are not specific to the group of men with less than a high school education but are common to all demographic groups.

The crosses in Figure 2 illustrate how cohort and age effects interact in the determination of trend unemployment over the life-cycle of a group that enters in 1976. Relative to those that entered in 1960 this group has a permanently higher trend unemployment rate, about 1 percentage point. Over the next ten years their trend rate first increases and then declines with the 1980s recession. Once they turn 35 years old their trend unemployment rate declines, but it is still about 1 percentage point higher than it was for that age group at the time the cohort entered in 1976. At the time this cohort gets close to retirement their age effect is about the same as it was for that age group in 1976.

4.2 LFP rates: cycle and trend

We now turn to the results on the trend in the labor force participation rate. In the estimation, we decompose each groups' LFP rate into a cyclical component, and cohort and age components. The cyclical component is the groups' response to the estimated cyclical indicator from the unemployment rate model. We call LFP rates pro-cyclical if they are negatively correlated with the cyclical indicator, that is, the LFP rate increases as the cyclical unemployment rate declines.

In Table 4 we report the cyclical response of LFP rates for the different demographic groups. The response is the sum of the coefficients on the cyclical indicator (contemporaneous and one lag and lead) with corresponding standard deviations in parentheses. For almost all demographic groups the LFP rate is pro-cyclical. Exceptions are college educated men older than 65 and women older than 55. The response coefficients tend to be small, except for the very young and the very old college educated groups. But even among the latter groups the response coefficients are statistically significant only for the 16-19 year old ones.

In Table 5 we report changes in the groups' trend LFP rates from 1979 to 2017. Like Table 3 for the group unemployment rates this exercise replicates the exercise from the

[9] We have estimated a constrained version of our model with fixed age and cohort effects, which is closer to the approach of Aaronson et al and CBO. The fit of the constrained model is significantly worse, and the inferred cohort effects are extremely volatile.

[10] The fact that we observe medium-run swings in age and cohort effects makes us more comfortable with not including deterministic drift terms in the laws of motion for age and cohort effects.

introduction, Table 1, with a finer demographic grid and a more systematic removal of cyclical effects. Given the limited cyclical volatility of LFP rates it should not be surprising that the two exercises yield the same results.

The largest trend decline of LFP rates occurs for those 16-24 years old. In particular, for the very young the trend LFP declines by more than 20 percentage points, most of it due to cohort effects.

For men, the trend LFP rates decline for all age and education groups with the largest declines among those younger than 65 and with less than a college degree. For example, for those with a high school degree trend LFP rates decline by about 10 percentage points. LFP rates of men 65 and older or with a college degree decline by much less. For most groups the age effect is the largest contributor to the decline in trend LFP rates, but there are also a number of notable cohort effects among prime-age males with a high school or some college education.

For women the trend LFP rates increased for all age and education groups with the largest increases among those with more than a high school education. For example, for those with a college degree LFP rates increased between 8 and 16 percentage points. Relative to men, cohort effects are more often the largest contributor to the increase in trend LFP rates, especially for college educated women, but even for women age effects remain the main reason for trend changes in a large number of groups. Unlike for changes in trend unemployment rates, age and cohort effects mostly work in the same direction.

Figure 3 shows the estimated cohort and age effects for women with a college school education. Clearly, the age effect is not constant over time. It has been trending downward for 25-54 year old individuals and exhibited a U-shape for the older groups. Increasing cohort effects are important for women entering prior to the 1980s, but afterwards cohort effects are relatively stable. Unlike for unemployment rates, estimates of age and cohort effects for LFP rates are relatively precise. Based on the two standard deviation error bands, the dashed lines in Figure 3, the changes in age and cohort effects over time are significant. And these narrower error bands for estimated age and cohort effects of LFP rates are common to all demographic groups.

The crosses in Figure 3 again illustrate how cohort and age effects interact in the determination of trend LFP over the life-cycle of a group that enters in 1976. Relative to those that entered in 1960 this group has a permanently higher trend LFP rate, about 7 percentage points. Over the next twenty years their trend rate increases noticeably, by about 10 percentage points. That is, when they turn 45 years old their trend LFP rate is about 10 percentage points higher than it was for that age group in 1976. As usual the LFP rate declines once this group reaches age 55.

5 Aggregate Unemployment and LFP Trend

We use the groups' population shares and our estimates of the groups' trend unemployment and LFP rates to construct the trend for the aggregate unemployment and LFP rate. The aggregate LFP rate is substantially less cyclical than the aggregate unemployment rate, and the cyclical components of the two rates are negatively correlated. The relative contributions of group trend rates and demographic factors to the trends of the aggregate unemployment and LFP rate differ. On the one hand, trends in group LFP participation rates and changes in the demographic composition all make important contributions to the trend of the aggregate LFP rate. On the other hand, the trend for aggregate unemployment rate is mainly driven by demographic changes and not by changes in group trends for unemployment and LFP rates. Finally, we use projections of the groups' population shares and trend rates to construct the projection of the aggregate trends. Over the next ten years we project a further decline of one percentage point for the trend LFP rate and half a percentage point for the trend unemployment rate.

We first discuss the aggregate LFP rate which is a simple population share weighted average of the group LFP rates, equation (2). The aggregate LFP rate increased from 1976 on, reaching its peak just prior to 2000, and declined thereafter; Figure 4, black line for actual and red line for trend. After flattening in 2005-06, the decline accelerated during and following the 2007-09 recession. The actual LFP rate does not deviate much from trend, it falls weakly below trend in recessions, that is, it is weakly pro-cyclical. In 2015, the decline of the LFP rate plateaued, but we project the trend to continue its fall over the next ten years to 61% in 2025, dotted red line in Figure 4.[11] The estimates of the trend LFP rate are quite precise, with the two standard deviation error bands barely noticeable, dashed lines in Figure 4.

We construct two counterfactual trend rates to demonstrate how the trend in the aggregate LFP rate depends on changes in group LFP rates and the demographic composition of the population. For the first counterfactual trend, we fix the population shares by age, gender, and education at their 2000 values, and use our estimates of the LFP rate trends for each demographic group, blue line in Figure 4. The counterfactual trend retains the hump shaped path, that is, it reflects the increasing trend for LFP rates of women prior to 2000, and the declining trend for LFP rates of young groups post-2000. Prior to 2000 the counterfactual exceeds the trend path which means that from 1976 to 2000 the population composition was changing towards groups with higher participation rates. The main driver of this process was increased educational attainment as we can see from a comparison with

[11] For the details of the projection see the Appendix.

our second counterfactual trend. For this counterfactual trend we fix the educational distribution conditional on age and gender at its 2000 values, and we use the actual population shares by age and gender and the trend group LFP rates, green line in Figure 4. Prior to 2000 this second counterfactual trend is pretty close to the first counterfactual, that is, changes in the age distribution alone have a minor impact on the trend aggregate LFP rate. Taking the actual population shares, that is, introducing the actual educational attainment of the population, then moves the second counterfactual trend to the trend, from the green to the red line. Thus the higher educational attainment of the 2000 population is the main reason for the boost of the aggregate LFP rate trend.

A similar comparison of the trend with the two counterfactual trends for the post-2000 period shows that increased educational attainment counteracted much of the widely discussed impact of population ageing on the LFP rate. Wheras the ageing of the population contributes to an almost three percentage point decline of the trend LFP rate in 2017, the difference between the blue and green lines, the increased educational attainment eliminates two percentage points of this gap, the difference between the green and red line.

We now proceed to the aggregate unemployment rate which is a nonlinear function of population share weighted group unemployment and LFP rates, equation (3). Figure 5 displays the actual unemployment rate and our trend estimate, solid red and black lines, together with our projection of its trend ten years out, dotted red line. Despite the apparent stability of the trends in group unemployment rates we observe a noticeable monotonic decline of the trend in the aggregate unemployment rate: from 7% in 1976 to 4.5% in 2017, a 2.5 percentage point drop, and it is projected to further decline to 4.2% by 2028. Relative to estimates of group trend unemployment rates, the uncertainty associated with the estimate of the aggregate trend unemployment rate is smaller. The two standard deviation error bands of the trend unemployment rate estimates, dashed red lines, from the beginning and end of sample do not overlap.

Compared to the cyclicality of the LFP rate, the cyclical deviations of the unemployment rate from its trend are large. Given the decline in the trend unemployment rate, the deviation of the actual unemployment rate from its trend value following the 2007-09 recession is exceptional, even when compared to the early 1980s recession. By 2016 the unemployment rate has returned to trend, and in 2017 the unemployment rate is marginally below its trend, especially when compared with previous periods of below trend unemployment rates.

In order to understand the relative contributions of changes in the trends of group unemployment and LFP rates and population shares to changes in the trend of the aggregate unemployment rate we construct three counterfactual aggregate trends. For the first counterfactual trend we use our estimates of the groups' trend unemployment rates, and fix the groups' trend LFP rates and population shares for age, gender, and education, at their 2000 values, the dark blue line in 5. This counterfactual trend is quite stable for the sample period, that is, the limited changes in the groups' trend unemployment rates that we discussed in the previous section have only a small impact on the aggregate trend. For the second counterfactual trend, we replace the fixed trend LFP rates from 2000 with their estimated time path in the first counterfactual, the green line in 5. Despite the large changes in the trends of group LFP rates this has only a limited impact on the trend of the aggregate unemployment rate, the green line stays close to the blue line. For the third counterfactual we use our estimates of the groups' trend unemployment and LFP rates together with the actual population shares by age and gender, but fix the distribution of educational attainment conditional on age and gender at its 2000 values, the light blue line in 5. This third counterfactual trend starts out at 6.3% in 1976 and ends at 5% in 2017, that is, the ageing of the population accounts for 1.3 percentage points or about half of the decline in the trend unemployment rate. The remaining part, the move from the light blue to the red line, then reflects the contribution from increased educational attainment of the population since 1976 and accounts for about two fifths of the decline in the trend unemployment rate. To summarize, the decline in the trend of the aggregate unemployment rate is mainly driven by demographic factors, about half of it attributable to the population getting older and most of the rest attributable to the population getting more educated.

6 Conclusions

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7 Appendix: A cohort model for education

- The cohort model for education is only needed to generate forecasts of the trend unemployment rate or LFP rate.

- We split the population into two groups, the young ones who are not differentiated by education and the mature ones who are. For the first group we have observations on population shares p and activity rates q by age groups,

$$\left\{p_{j,t}, q_{j,t}^{0} : \text{for age groups } A_j \text{ with } j = 1, .., J_E - 1\right\}$$

In particular, the age groups are A_1 (16-19 year olds), and A_2 (20-24 years old). For the mature population we have population shares, educational attainment shares, and activity rates by age groups,

$$\left\{p_{j,t}, w_{j,t}^{e}, q_{j,t}^{e} : \text{for age groups } A_j^e \text{ with } j = J_E, .., J \text{ and education groups } e \in E\right\}.$$

In particular, the age groups are A_3 (25-34 year old), A_4 (35-44), A_5 (45-54), A_6 (55-64), and A_7 (65+). There are four education groups, $E = \{< HS, HS, < C, C+\}$, and $w_{j,t}^{e}$ is the share of those in that age group with education e.

- We assume that there is an initial entry value for all education levels at age $i_E = \min\{A_{J_E}\}$. We assume that the education shares for age groups evolve according to a cohort model with no age effects

$$\begin{aligned}
\bar{w}_{j,t}^{e} &= \frac{1}{\#A_j} \sum_{i \in A_j} w_{i,t}^{e} + \bar{\varepsilon}_{jt}^{e} \text{ with } \bar{\varepsilon}_{jt}^{e} \sim N\left(0, \bar{\sigma}_{e,j}^{2}\right) \qquad (4)\\
i_E &: w_{i_E,t}^{e} = w_{i_E,t-1}^{e} + \varepsilon_{i_E,t}^{e} \text{ with } \varepsilon_{i_E t}^{e} \sim N\left(0, \sigma_{e,0}^{2}\right)\\
i &\in A_j : w_{i,t}^{e} = \delta_j^e + w_{i-1,t-1}^{e} + \varepsilon_{i,t}^{e} \text{ with } \varepsilon_{it}^{e} \sim N\left(0, \sigma_{e,1}^{2}\right)
\end{aligned}$$

The initial cohort effect of a new cohort is a random variation of the initial effect of the new cohort in the previous period. We allow for changes in the measured education shares for age groups other time due to measurement error or differential death rates across age groups (see Aaronson and Sullivan, 2001).

- The baseline model assumes no deterministic drift, $\delta_j^e = 0$. For the baseline model there appears to be drift in the education shares: in a cohort the shares of those with more than a HS education are increasing over time and the shares with a HS education or less are decreasing over time. Our baseline projections are based on no deterministic drift.

- We have estimated the model with non-zero drift terms, $\delta_j^e \neq 0$, but the estimates for the drift terms tend to be not significant. Allowing for non-zero deterministic drift terms affects the projection of future LFP rate trends, the projected LFP rate tends to decline less.
- We have estimated model (3) allowing for a cyclical effect on the entry shares $w_{i_E}^e$. For this we have used several lags of the aggregate unemployment rate, but the estimated cyclical effects are not significant.
- Appendix Figure Figure 6 shows cohort effects for education shares.

Table 1: Unemployment, Labor Force Participation, and Demographics, 1979 and 2017

	(1) Men, 25-54	(2) Men, 55+	(3) Women, 25-54	(4) Women, 55+
		(A) Unemployment Rate		
		1979		
HS or less	4.4	3.4	6.4	3.4
More than HS	2.1	2.1	3.9	2.8
		2017		
HS or less	5.3	4.1	6.4	3.6
More than HS	2.8	2.9	3.1	3.4
		(B) LFP Rate		
		1979		
HS or less	93.0	42.9	58.6	21.7
More than HS	96.4	60.5	70.3	30.7
		2017		
HS or less	83.8	39.8	63.7	26.1
More than HS	91.8	51.2	80.5	42.6
		(C) Population Shares		
		1979		
HS or less	18.1	12.0	22.5	16.2
More than HS	13.3	3.4	11.0	3.5
		2017		
HS or less	11.2	8.2	9.4	10.2
More than HS	17.3	11.3	19.9	12.4

Note: Table shows data for 1979 and 2017, years with unemployment troughs at the beginning and end of sample; population 25 years and older.

Table 2: Cyclical Response of Unemployment Rates

	(1) All	(2) <HS	(3) HS	(4) <COL	(5) COL+
			Male		
20-24	0.75	x	x	x	x
	(0.04)				
35-44		0.91	0.76	0.80	0.95
		(0.06)	(0.04)	(0.04)	(0.07)
45-54		0.82	0.68	0.82	0.96
		(0.06)	(0.04)	(0.04)	(0.08)
55-64		0.70	0.64	0.73	0.91
		(0.05)	(0.04)	(0.04)	(0.09)
65+		0.28	0.33	0.60	0.72
		(0.06)	(0.04)	(0.08)	(0.13)
			Female		
20-24	0.67	x	x	x	x
	(0.03)				
35-44		0.85	0.76	0.77	0.90
		(0.07)	(0.05)	(0.04)	(0.09)
45-54		0.72	0.65	0.70	0.88
		(0.06)	(0.04)	(0.05)	(0.08)
55-64		0.48	0.60	0.74	0.83
		(0.05)	(0.04)	(0.06)	(0.09)
65+		0.27	0.41	0.71	0.68
		(0.05)	(0.06)	(0.09)	(0.14)

Note: The age groups 16-24 are not differentiated by education. The cyclical response of age groups 16-19 and 25-34 is normalized to one. Standard deviations in parenthesis.

Table 3: Change of Trend Unemployment Rates from 1979 to 2017

	(1) All	(2) <HS	(3) HS	(4) <COL	(5) COL+
			Male		
16-19	0.2				
	(0.0, 0.2)				
20-24	0.1				
	(0.0, 0.1)				
25-34		-1.4	0.3	-0.8	-0.7
		(-1.0, -0.4)	(-0.0, 0.3)	(-0.4, -0.4)	(-0.1, -0.6)
35-44		-0.7	0.3	0.4	-0.2
		(-0.7, -0.0)	(-0.0, 0.3)	(-0.3, 0.6)	(-0.1, -0.1)
45-54		0.9	0.3	-0.0	0.0
		(-0.0, 0.9)	(-0.0, 0.3)	(-0.2, 0.2)	(-0.0, 0.1)
55-64		1.1	0.1	0.3	0.7
		(0.7, 0.4)	(0.0, 0.1)	(0.0, 0.3)	(0.0, 0.7)
65-79		1.4	0.1	0.3	0.8
		(0.5, 0.9)	(0.0, 0.1)	(0.3, -0.0)	(0.0, 0.7)
			Female		
16-19	-0.5				
	(-0.6, 0.0)				
20-24	-0.7				
	(-0.7, -0.1)				
25-34		-0.6	-0.2	-0.9	-2.6
		(-0.6, -0.0)	(-0.0, -0.2)	(-0.2, -0.7)	(-2.3, -0.3)
35-44		-0.6	0.3	0.0	-2.1
		(-0.8, 0.2)	(-0.0, 0.3)	(-0.2, 0.2)	(-1.9, -0.1)
45-54		0.3	0.0	-0.3	-1.1
		(0.4, -0.0)	(-0.0, 0.0)	(-0.2, -0.1)	(-1.2, 0.1)
55-64		0.7	0.0	0.1	-0.0
		(1.1, -0.4)	(-0.0, 0.0)	(-0.1, 0.2)	(-0.4, 0.4)
65-79		1.0	0.2	0.8	0.4
		(0.5, 0.5)	(0.0, 0.2)	(0.0, 0.8)	(0.3, 0.1)

Note: For each demographic group we calculate the percentage point change in the trend unemployment rate from 1979 to 2017. The first (second) number in parentheses denotes the contribution from the cohort (age) effect. The age groups 16-24 are not differentiated by education.

Table 4: Cyclical Response of LFP Rates

	(1) All	(2) <HS	(3) HS	(4) <COL	(5) COL+
			Male		
16-19	-0.53	x	x	x	x
	(0.10)				
20-24	-0.19	x	x	x	x
	(0.08)				
25-34		-0.12	-0.13	-0.25	-0.32
		(0.10)	(0.10)	(0.11)	(0.20)
35-44		0.02	-0.00	-0.08	-0.10
		(0.10)	(0.09)	(0.11)	(0.19)
45-54		-0.03	-0.01	-0.15	-0.08
		(0.10)	(0.09)	(0.11)	(0.19)
55-64		-0.03	-0.19	-0.14	-0.17
		(0.11)	(0.10)	(0.13)	(0.25)
65-79		-0.11	-0.13	0.08	0.54
		(0.10)	(0.10)	(0.14)	(0.31)
			Female		
16-19	-0.77	x	x	x	x
	(0.14)				
20-24	-0.21	x	x	x	x
	(0.11)				
25-34		-0.15	-0.15	-0.27	-0.07
		(0.13)	(0.16)	(0.20)	(0.38)
35-44		-0.27	0.03	-0.17	0.17
		(0.12)	(0.16)	(0.20)	(0.38)
45-54		-0.08	0.10	0.01	-0.50
		(0.11)	(0.16)	(0.20)	(0.37)
55-64		0.15	0.02	0.08	0.10
		(0.11)	(0.16)	(0.22)	(0.43)
65-79		-0.01	-0.01	0.16	0.32
		(0.09)	(0.15)	(0.19)	(0.36)

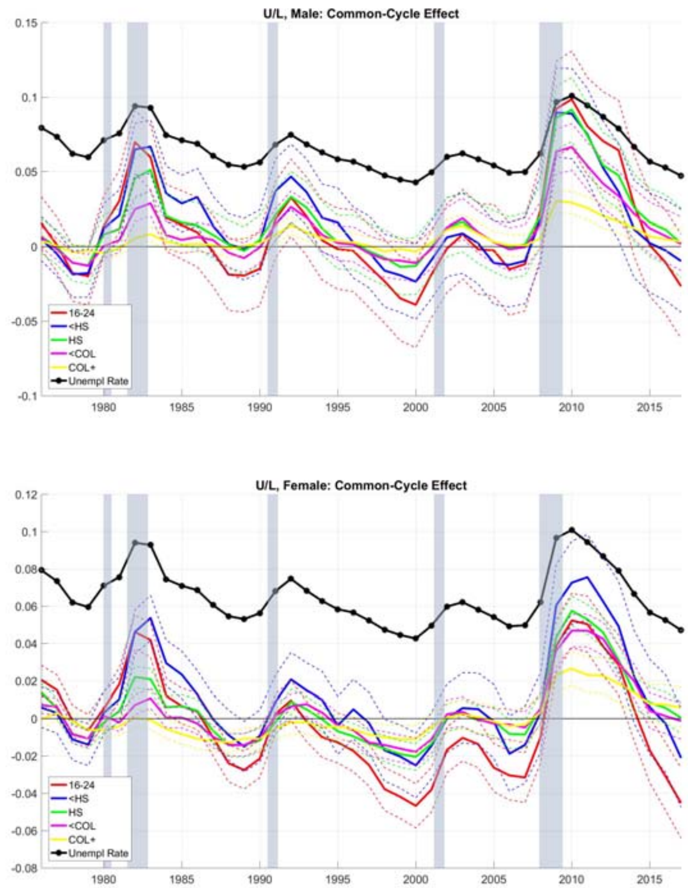
Note: For each demographic group the cyclical indicator (CI) is the estimated CI from the unemployment rate model. The response is the sum of the coefficients on the CI with corresponding standard deviations in parenthesis. The age group 16-24 is not differentiated by education.

Table 5: Change of Trend LFP Rate from 1979 to 2017

	(1) All	(2) <HS	(3) HS	(4) <COL	(5) COL+
			Male		
16-19	-27.8				
	(-19.5, -8.3)				
20-24	-12.7				
	(-16.4, 3.7)				
25-34		-9.5	-10.5	-5.8	-3.1
		(-1.8, -7.7)	(-7.0, -3.5)	(-4.3, -1.5)	(-0.0, -3.1)
35-44		-6.8	-9.8	-6.1	-2.5
		(-1.6, -5.2)	(-6.0, -3.8)	(-3.7, -2.5)	(-0.0, -2.5)
45-54		-9.6	-10.6	-6.7	-3.6
		(-2.2, -7.5)	(-4.1, -6.5)	(-1.9, -4.8)	(-0.0, -3.6)
55-64		-9.2	-10.2	-7.7	-4.0
		(-2.6, -6.6)	(-2.4, -7.7)	(-1.2, -6.5)	(-0.0, -4.0)
65-79		-1.7	-4.3	-2.0	-0.8
		(-1.4, -0.3)	(-1.2, -3.2)	(-0.4, -1.6)	(0.0, -0.8)
			Female		
16-19	-21.5				
	(-10.8, -10.7)				
20-24	-1.4				
	(-6.2, 4.8)				
25-34		1.5	4.8	9.0	8.2
		(-1.2, 2.8)	(-4.4, 9.2)	(-0.7, 9.7)	(1.7, 6.5)
35-44		0.2	2.8	10.5	10.1
		(1.1, -1.0)	(0.7, 2.0)	(4.0, 6.5)	(5.1, 5.0)
45-54		3.2	7.6	13.8	11.9
		(2.8, 0.5)	(6.1, 1.5)	(8.3, 5.4)	(7.9, 4.0)
55-64		2.6	8.9	12.3	16.4
		(2.4, 0.3)	(7.2, 1.7)	(8.9, 3.4)	(8.5, 7.8)
65-79		1.7	1.7	6.2	11.4
		(0.9, 0.8)	(2.9, -1.3)	(4.4, 1.9)	(4.6, 6.8)

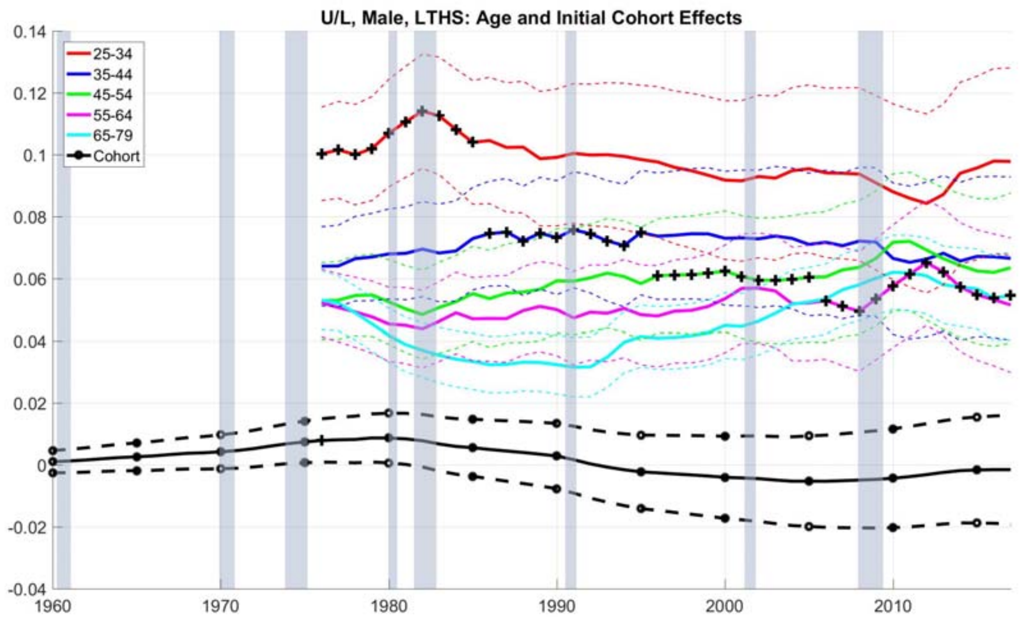
Note: For each demographic group we calculate the percentage point change in the trend unemployment rate from 1979 to 2017. The first (second) number in parentheses denotes the contribution from the cohort (age) effect. The age groups 16-24 are not differentiated by education.

Figure 1: Common Unemployment Cycle by Demographic Group



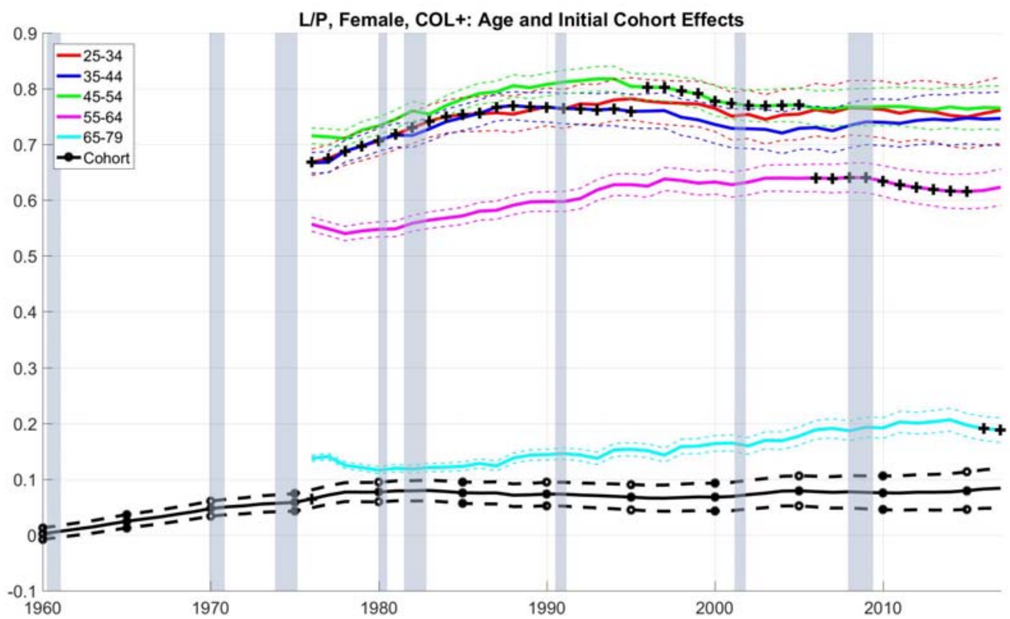
Note: Estimated cyclical effect for the age group 16-24 years old (not differentiated by education) and the demographic groups defined by gender and education. Dashed lines denote two standard error bands. The black line with circles is the overall unemploymen rate.

Figure 2: Cohort and Age Effects for Unemployment Rate of Males with Less Than High School Education



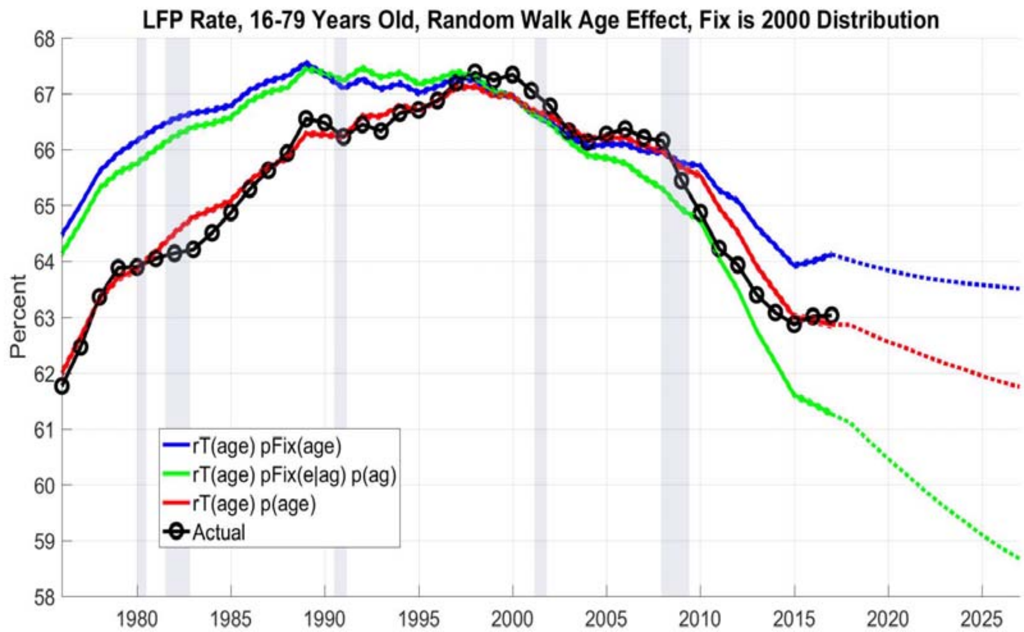
Note: Estimated cohort and age effects for groups aged 25-79 years. The crosses mark the life cycle of a group that enters in 1976. Dashed lines denote two standard error bounds based on the smoothed posterior estimates from the Kalman filter.

Figure 3: Cohort and Age Effects for LFP Rate of Females with College Education



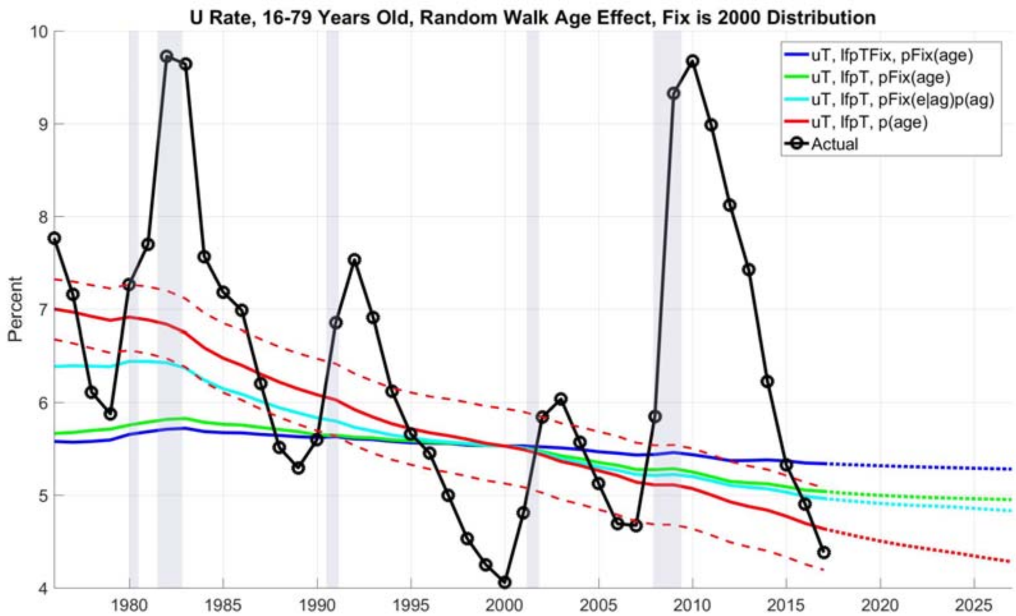
Note: Estimated cohort and age effects for groups aged 25-79 years. The crosses mark the life cycle of a group that enters in 1976. Dashed lines denote two standard error bounds based on the smoothed posterior estimates from the Kalman filter.

Figure 4: Labor Force Participation Rate Trend



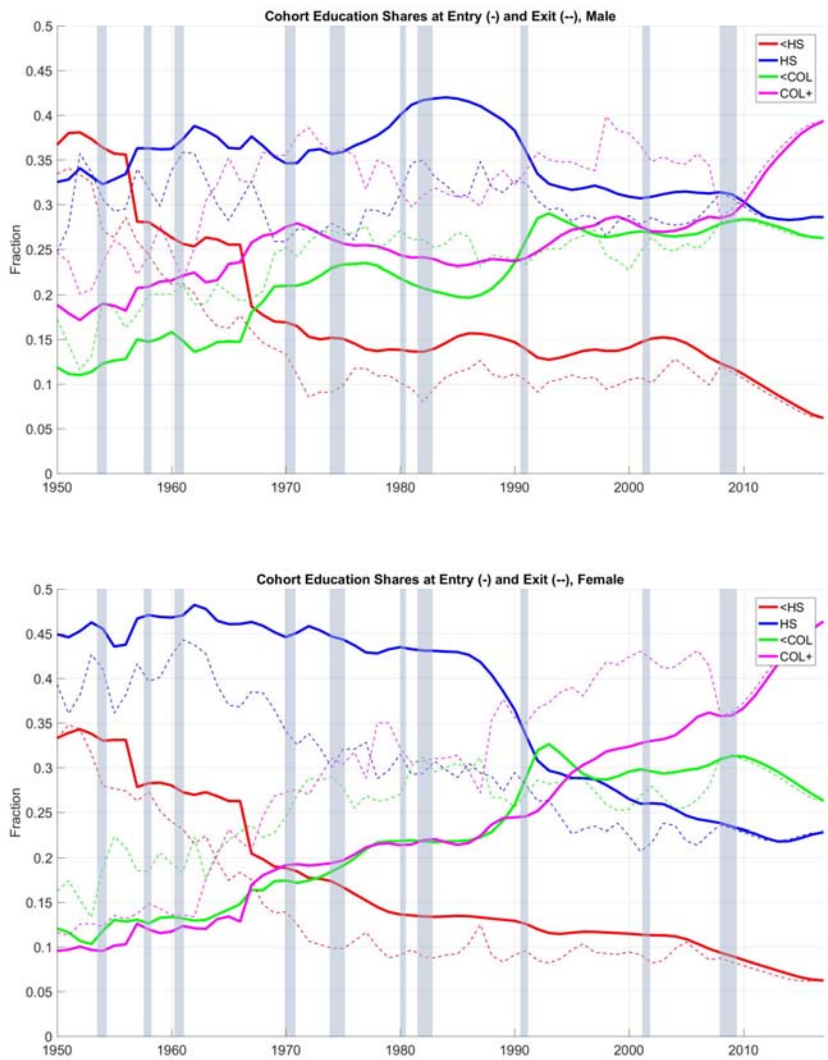
Note: The red line shows the estimated trend in the aggregate LFP rate. The blue line fixes the population distribution by age, gender, and education at its 2017 values and allows for variation of the LFP rate trend of each demographic group. The green line fixes the education distribution conditional on age and gender at its 2017 values and allows for variation of the LFP rate trend of each demographic group, and the population shares by age and gender. Dashed lines denote two standard error bounds based on the smoothed posterior estimates from the Kalman filter. Dotted lines denote forward projections of the trend LFP rates.

Figure 5: Unemployment Rate Trend



Note: The dark blue line fixes the trend LFP rate and the population shares by age, gender, and education at their 2017 values and allows for variation of the unemployment rate trend of each demographic group. The green line fixes the population shares at their 2017 values and allows for variation of the unemployment rate and LFP rate trends of each demographic group. The light blue line fixes the education distribution conditional on age and gender at its 2017 values and allows for variation of the unemployment rate and LFP rate trends and the population shares of each demographic group. The red line allows for variation in the trend values of the unemployment rate and LFP rate and the population shares of demographic groups. The dashed red lines denote a two standard deviation error band for the trend. Short dashed lines denote two standard error bounds based on the smoothed posterior estimates from the Kalman filter. Dotted lines denote forward projections of the trend unemployment rates.

Figure 6: Cohort Effects for Education Shares



Note: Solid lines denote the education share at the time a cohort enters the sample and dashed lines denote the education share at the end of the sample or at the time the cohort exits the sample.