Online Appendix

Unemployment, Participation and Worker Flows over the Life-Cycle

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A Conditional Analysis

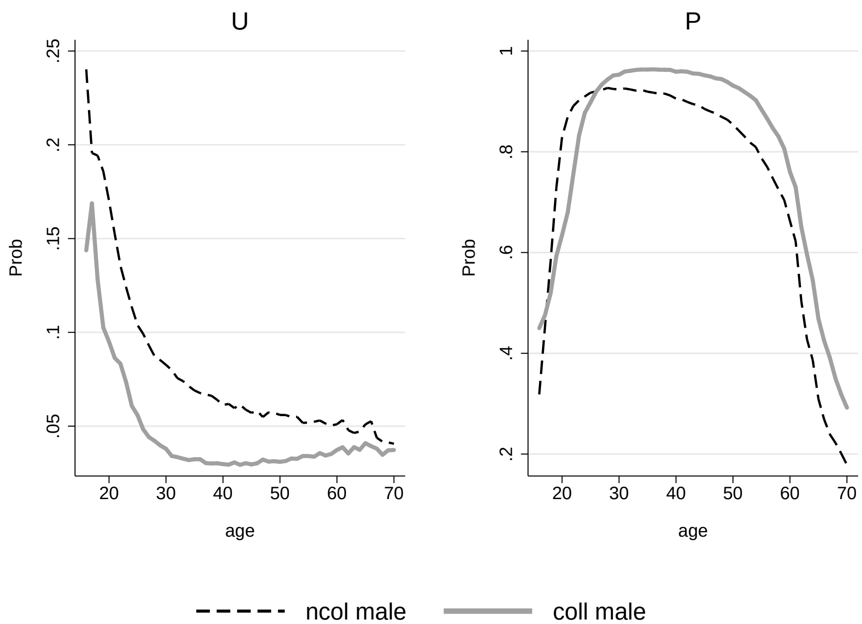
We present results of different subsamples of interest. We analysis the relative importance of each flow for several groups defined by educational attaintment, marital status, and child presence in the household. The evidence shows a remarkable consistence of baseline results across different samples.

A.1 Conditional Analysis by Educational Group and Gender

In this subsection, we consider two subsamples: individuals with at most a high school diploma (*ncol*) and individuals with at least one year of college education (*coll*).

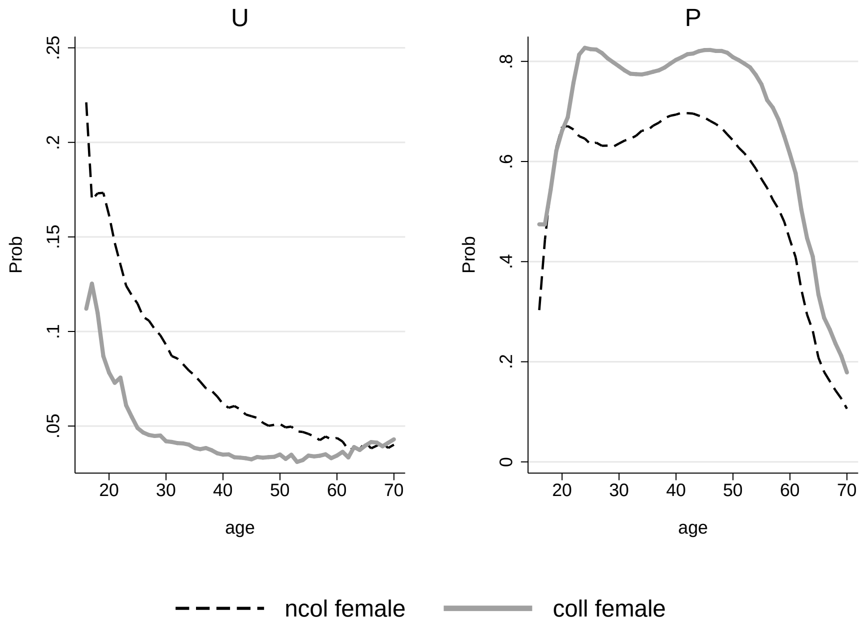
A.1.1 Estimated Flows and Stocks by Educational Group and Gender

Figure A1: Life-Cycle Unemployment and Participation Profiles: Males, Non-College vs College



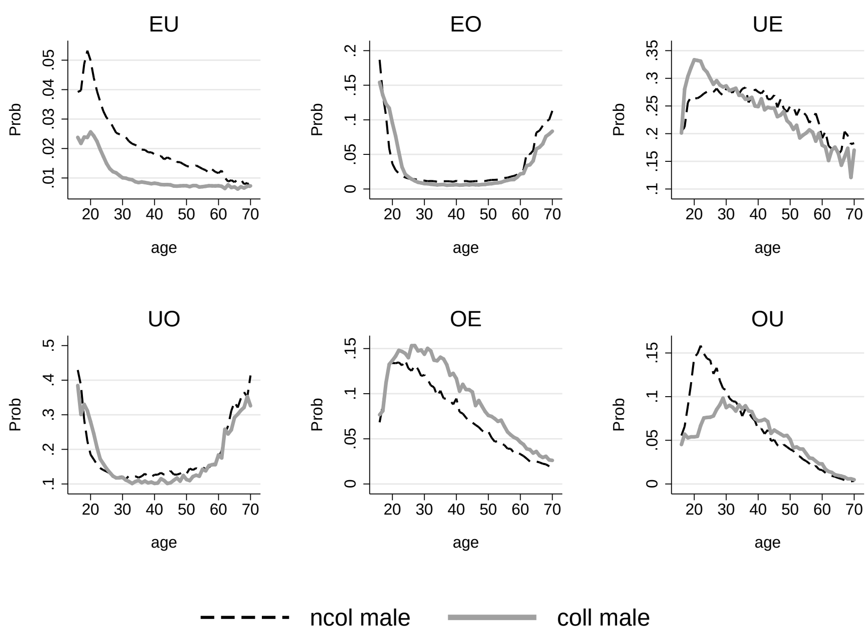
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A2: Life-Cycle Unemployment and Participation Profiles: Females, Non-College vs College



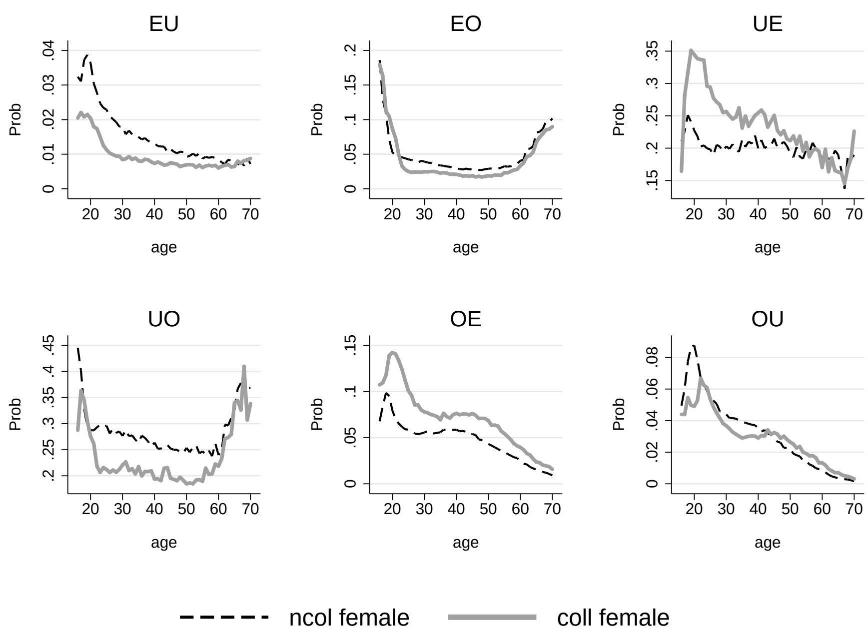
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A3: Life-Cycle Profiles of Worker Flows Transitions: Males, Non-College vs College



Note: Unconditional life-cycle profiles estimated via weighted OLS.

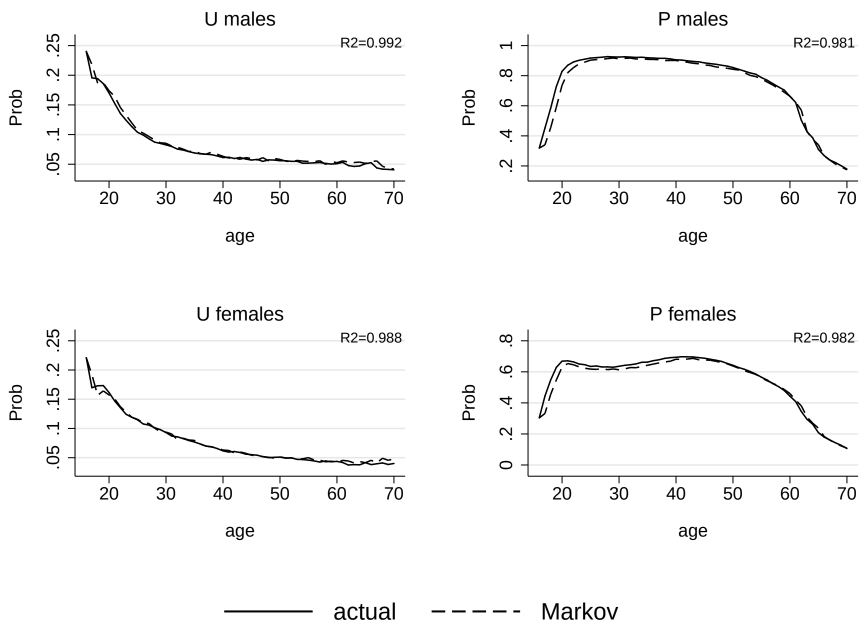
Figure A4: Life-Cycle Profiles of Worker Flows Transitions: Females, Non-College vs College



Note: Unconditional life-cycle profiles estimated via weighted OLS.

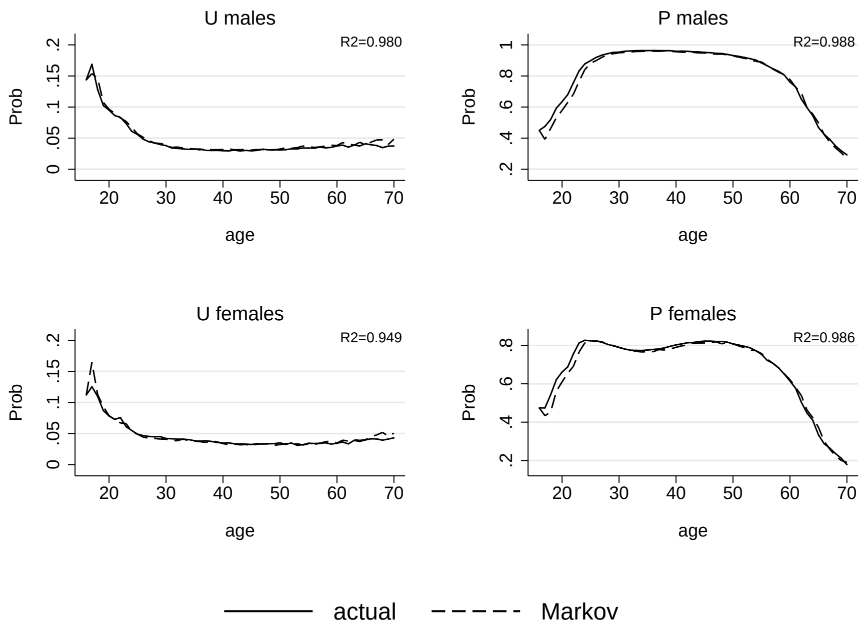
A.1.2 Markovian Simulations by Educational Group and Gender

Figure A5: Markov-Chain Simulated Unemployment and Participation: Non-College



Note: Unconditional life-cycle profiles estimated via weighted OLS.

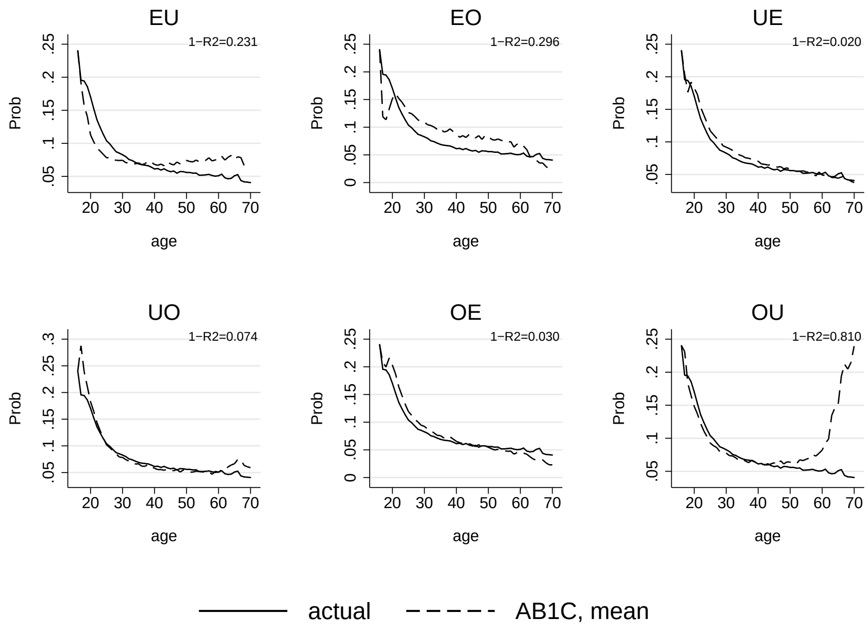
Figure A6: Markov-Chain Simulated Unemployment and Participation: College



Note: Unconditional life-cycle profiles estimated via weighted OLS.

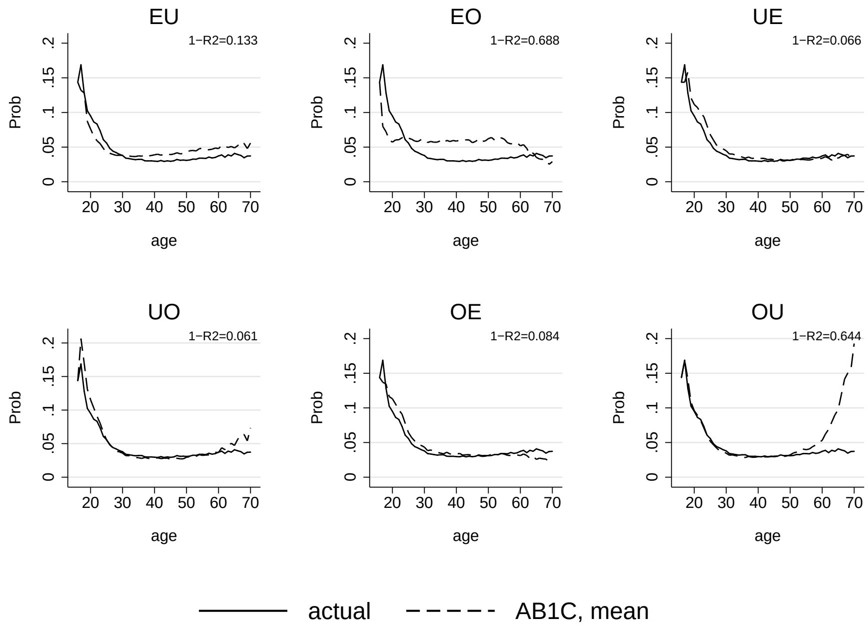
A.1.3 Importance Decomposition of Flows by Educational Group and Gender

Figure A7: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Non-College



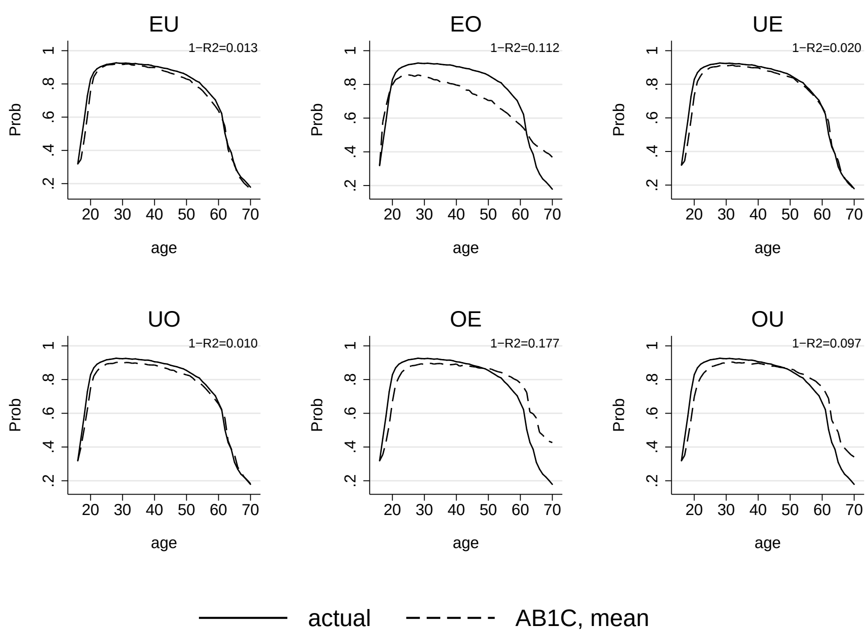
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A8: AB1C Decomposition of the Importance of Flows: Unemployment, Males, College



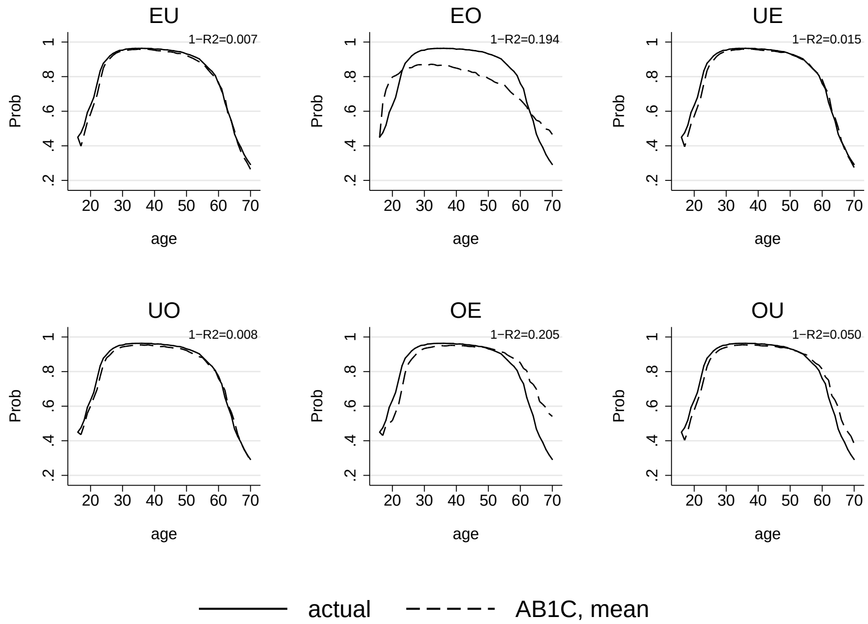
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A9: AB1C Decomposition of the Importance of Flows: Participation, Males, Non-College



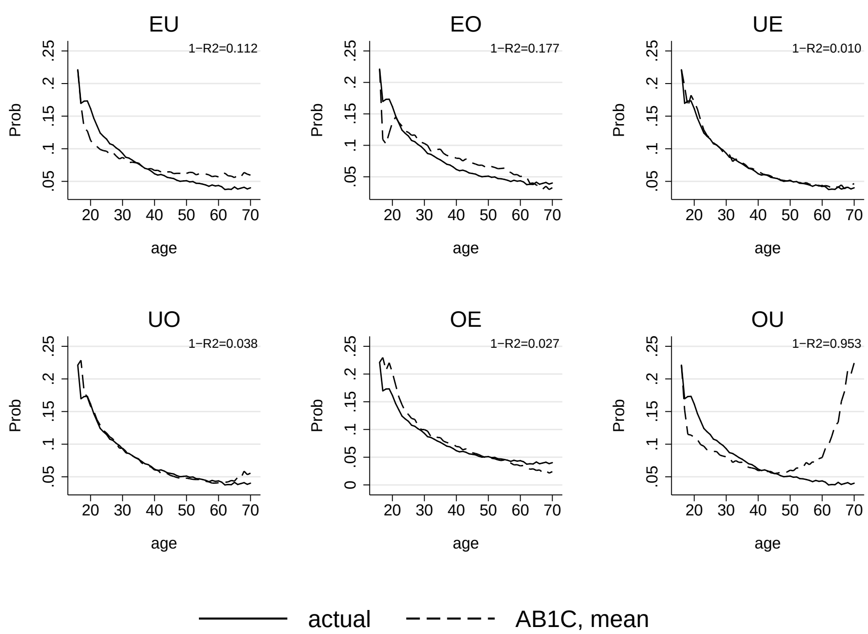
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A10: AB1C Decomposition of the Importance of Flows: Participation, Males, College



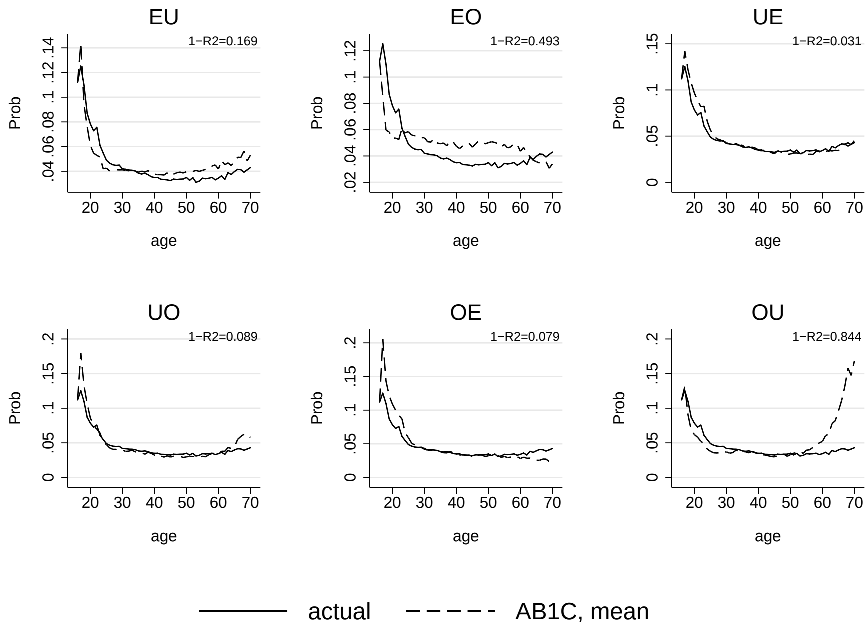
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A11: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Non-College



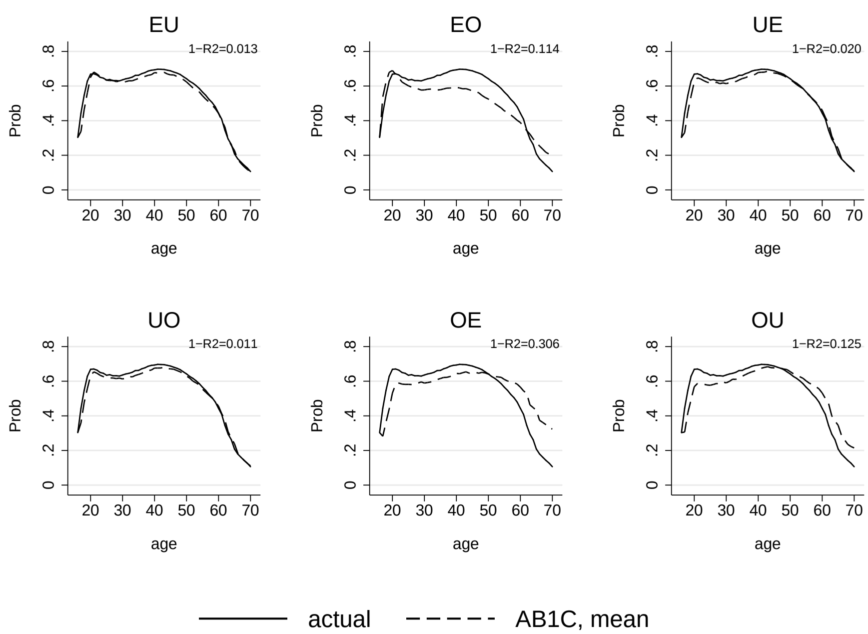
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A12: AB1C Decomposition of the Importance of Flows: Unemployment, Females, College



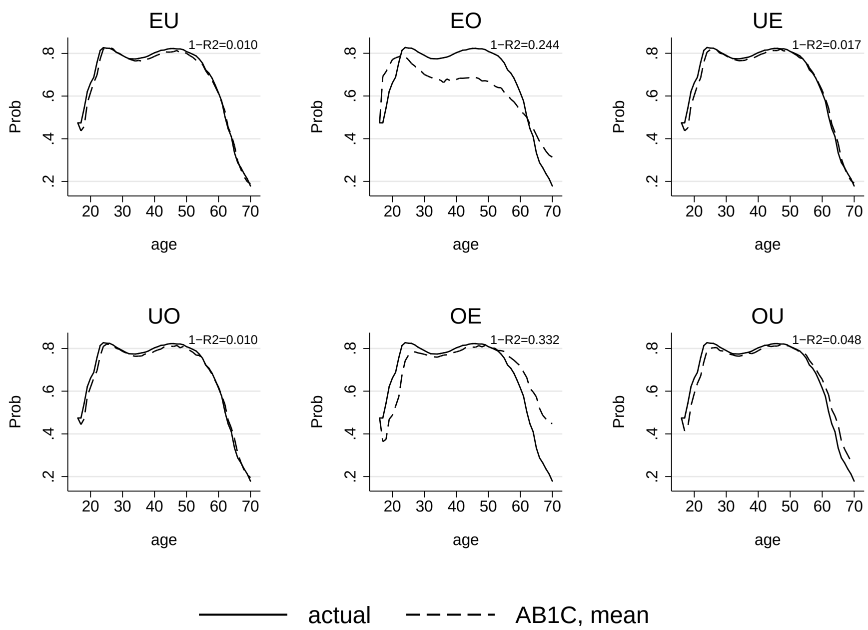
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A13: AB1C Decomposition of the Importance of Flows: Participation, Females, Non-College



Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A14: AB1C Decomposition of the Importance of Flows: Participation, Females, College



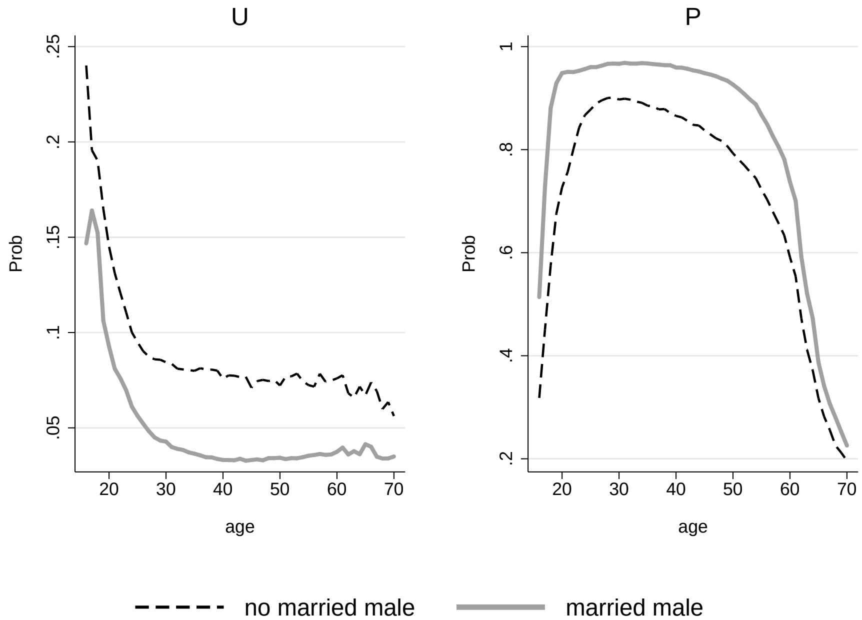
Note: Unconditional life-cycle profiles estimated via weighted OLS.

A.2 Conditional Analysis by Marital Status and Gender

In this subsection, we consider married and non-married individuals.

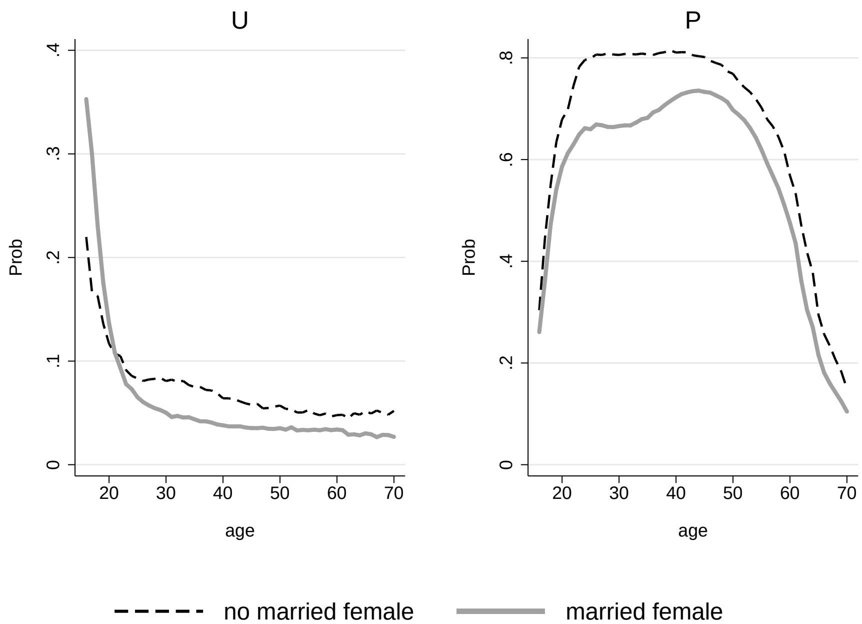
A.2.1 Estimated Flows and Stocks by Marital Status and Gender

Figure A15: Life-Cycle Unemployment and Participation Profiles: Males, Non-Married vs Married



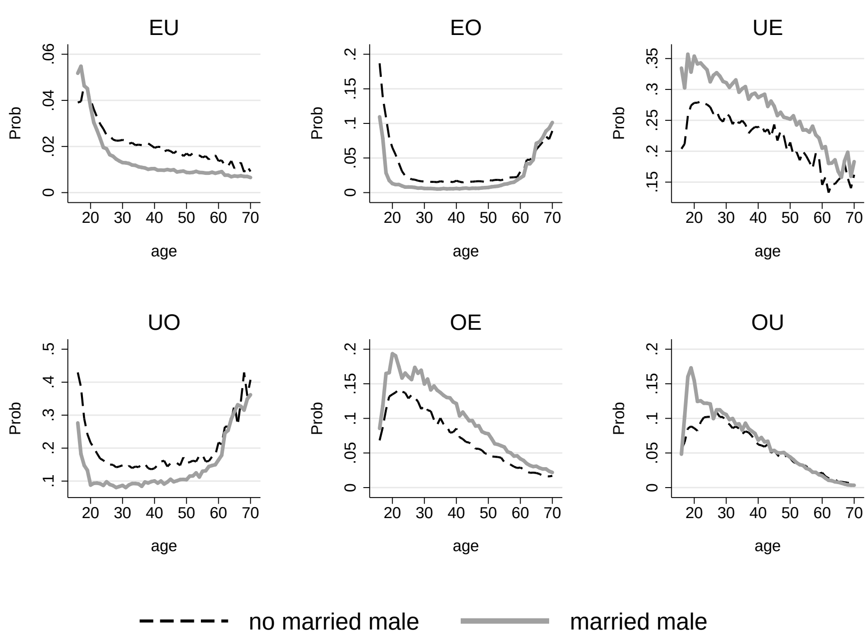
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A16: Life-Cycle Unemployment and Participation Profiles: Females, Non-Married vs Married



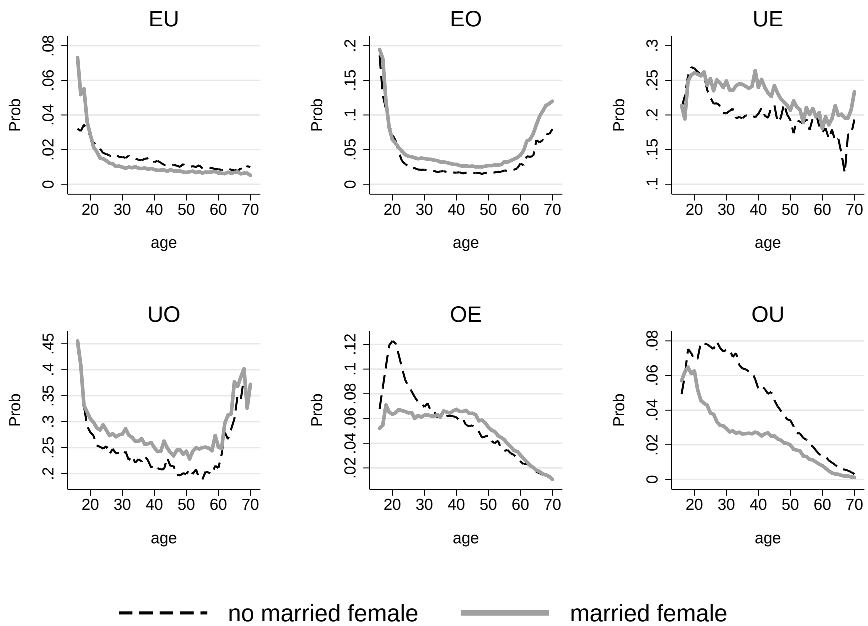
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A17: Life-Cycle Profiles of Worker Flows Transitions: Males, Non-Married vs Married



Note: Unconditional life-cycle profiles estimated via weighted OLS.

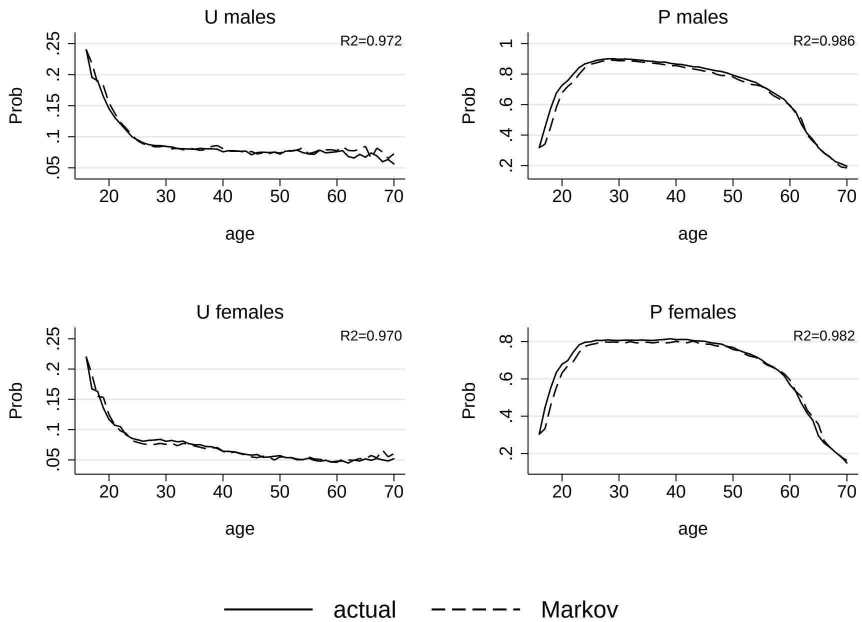
Figure A18: Life-Cycle Profiles of Worker Flows Transitions: Females, Non-Married vs Married



Note: Unconditional life-cycle profiles estimated via weighted OLS.

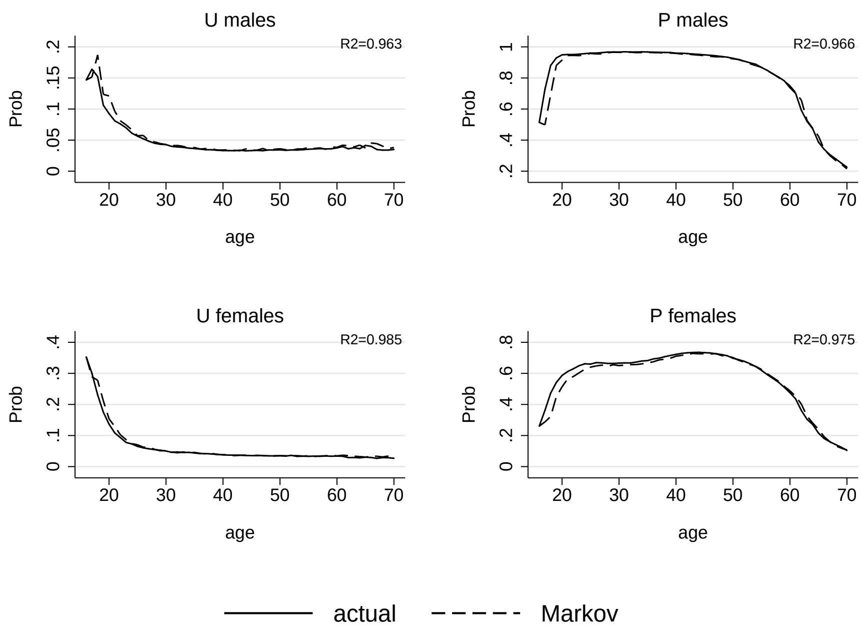
A.2.2 Markovian Simulations by Marital Status and Gender

Figure A19: Markov-Chain Simulated Unemployment and Participation: Non-Married



Note: Unconditional life-cycle profiles estimated via weighted OLS.

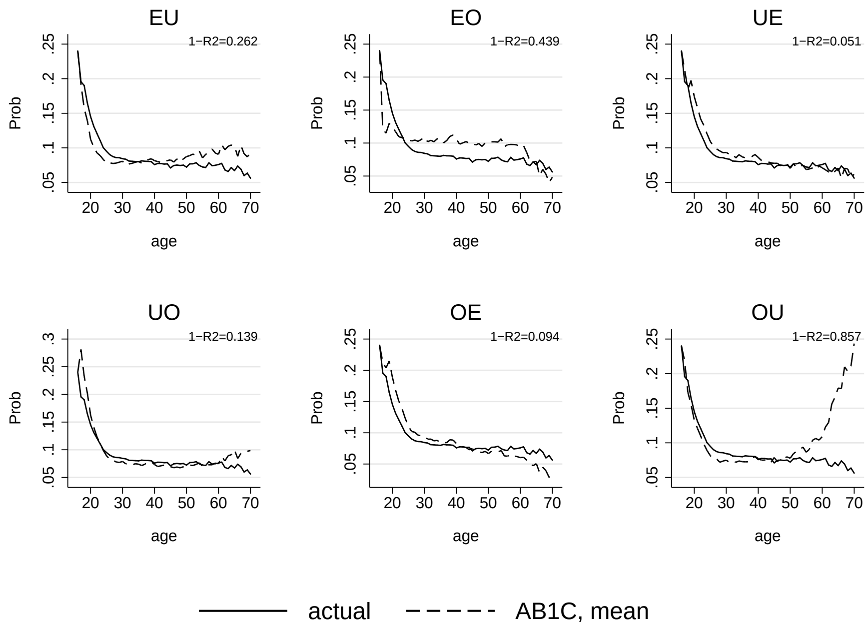
Figure A20: Markov-Chain Simulated Unemployment and Participation: Married



Note: Unconditional life-cycle profiles estimated via weighted OLS.

A.2.3 Importance decomposition of Flows by Marital Status and Gender

Figure A21: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Non-Married



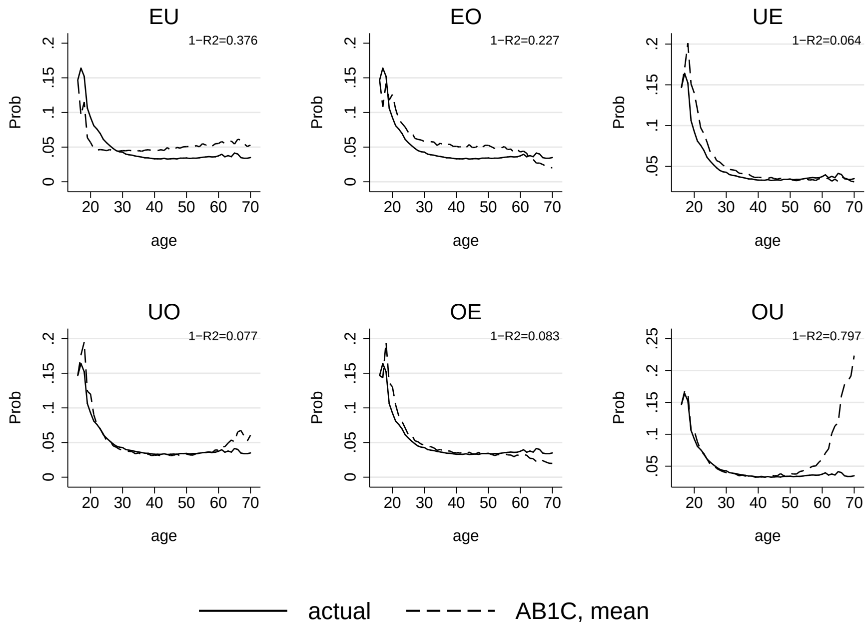
Note: Unconditional life-cycle profiles estimated via weighted OLS.

A.3 Conditional Analysis by Child Presence and Gender

In this subsection, we consider individuals with and without at least a child in their households.

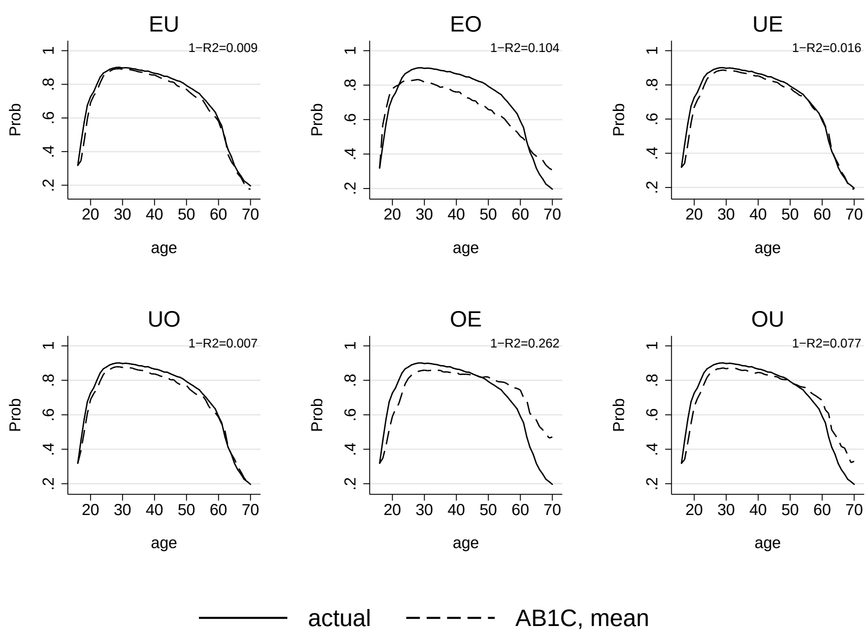
A.3.1 Estimated Flows and Stocks by Child Presence and Gender

Figure A22: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Married



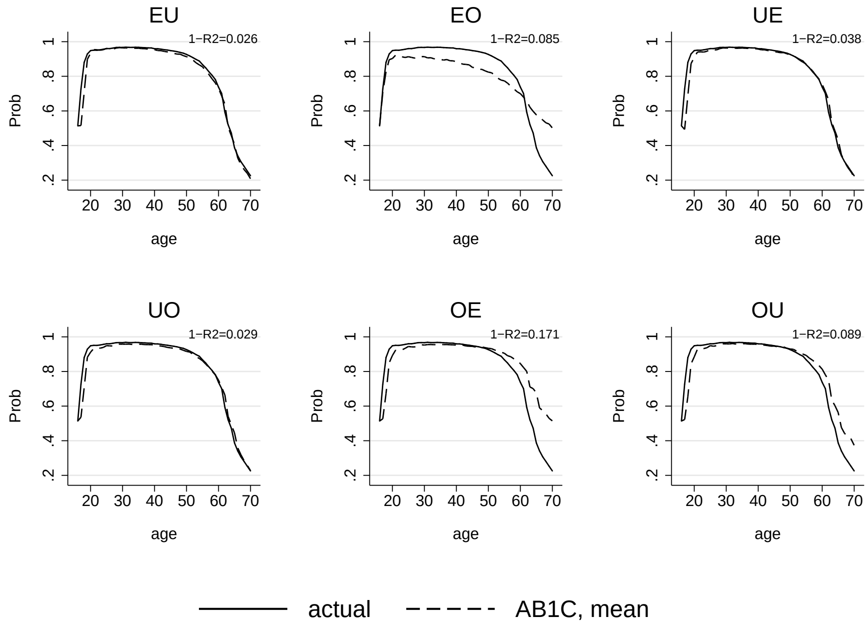
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A23: AB1C Decomposition of the Importance of Flows: Participation, Males, Non-Married



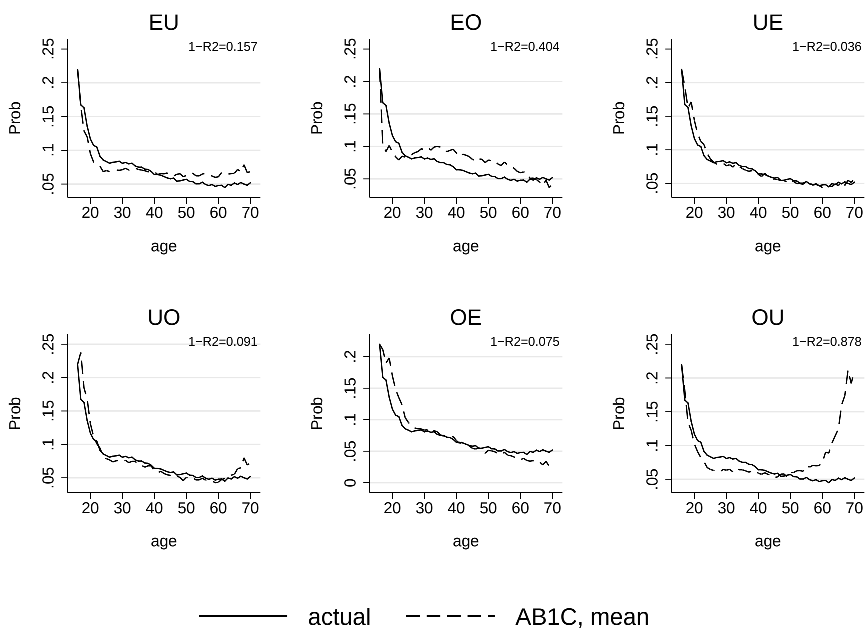
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A24: AB1C Decomposition of the Importance of Flows: Participation, Males, Married



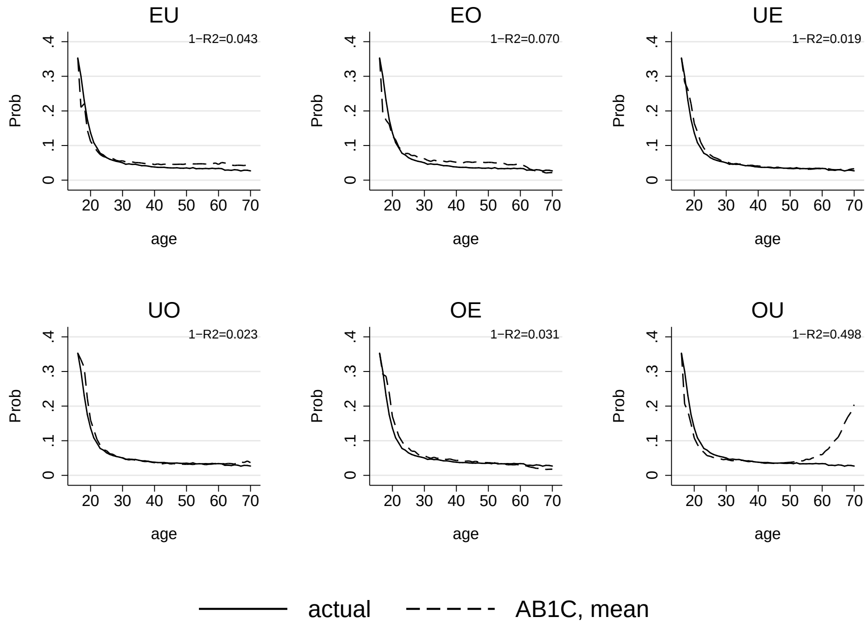
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A25: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Non-Married



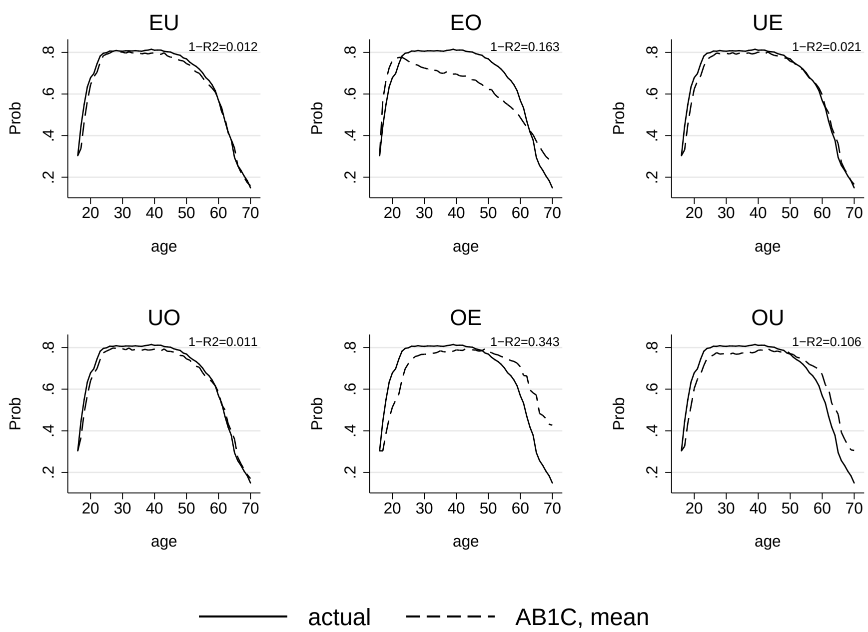
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A26: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Married



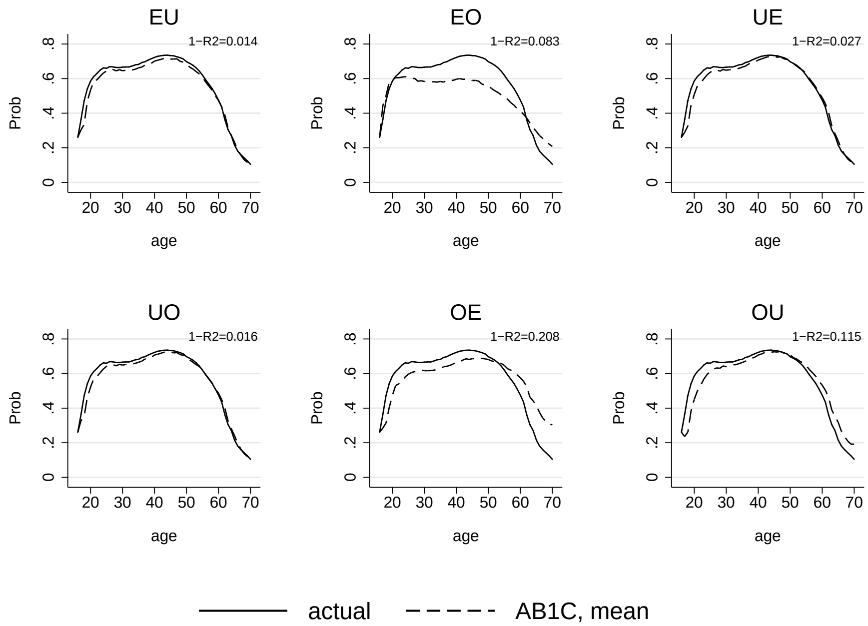
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A27: AB1C Decomposition of the Importance of Flows: Participation, Females, Non-Married



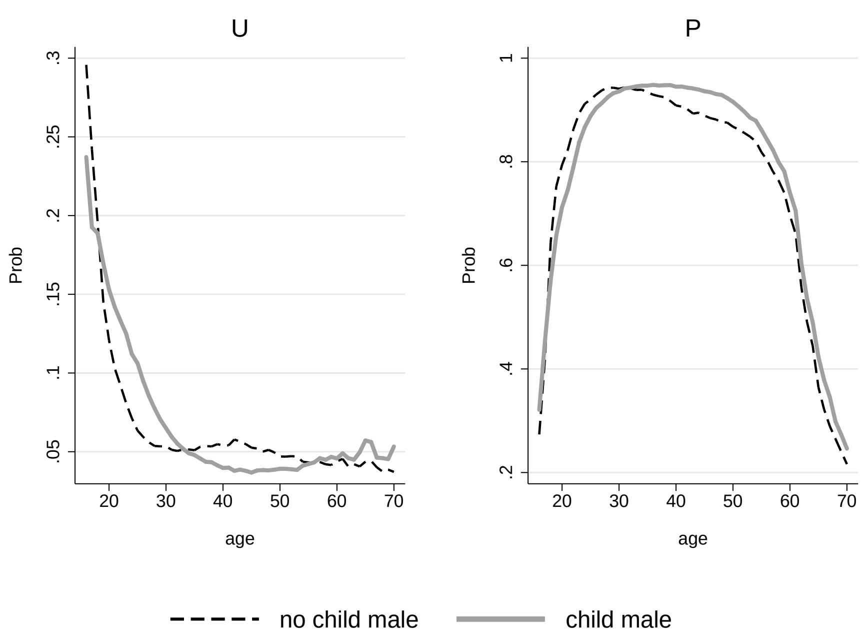
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A28: AB1C Decomposition of the Importance of Flows: Participation, Females, Married



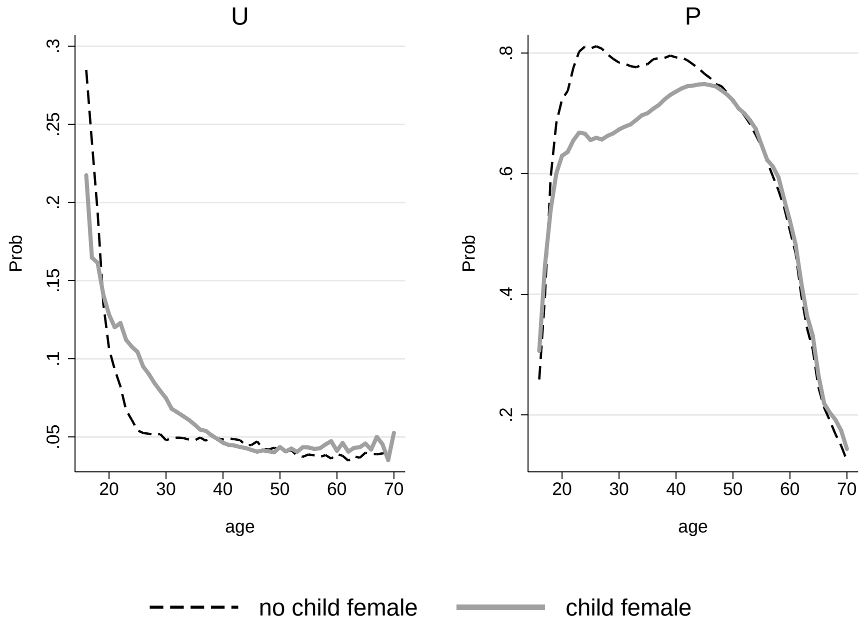
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A29: Life-Cycle Unemployment and Participation Profiles: Males, No-Child vs Child



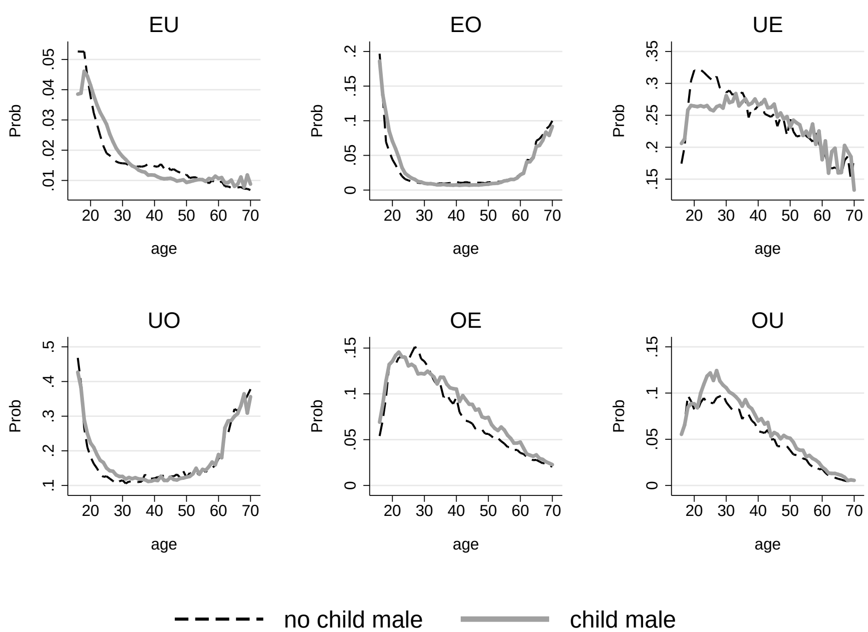
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A30: Life-Cycle Unemployment and Participation Profiles: Females, No-Child vs Child



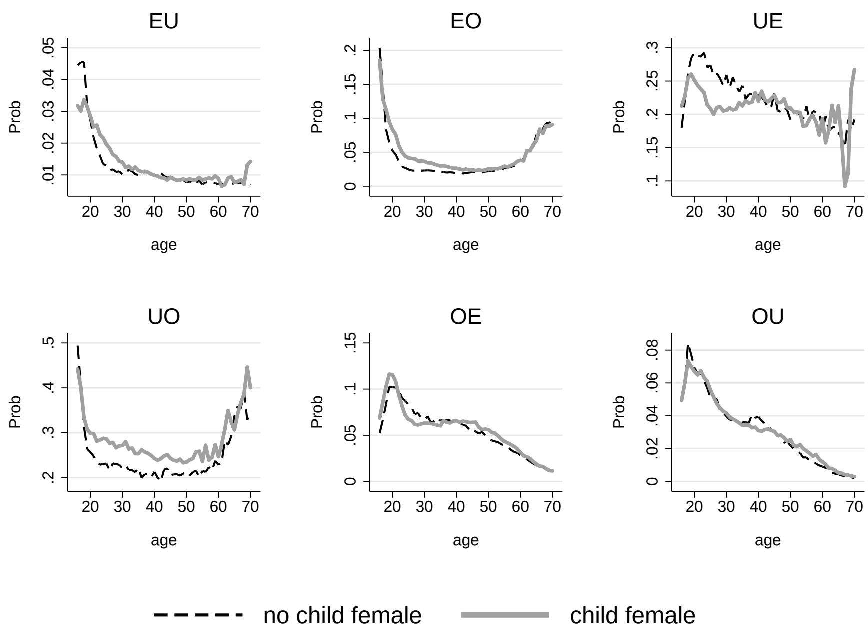
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A31: Life-Cycle Profiles of Worker Flows Transitions: Males, No-Child vs Child



Note: Unconditional life-cycle profiles estimated via weighted OLS.

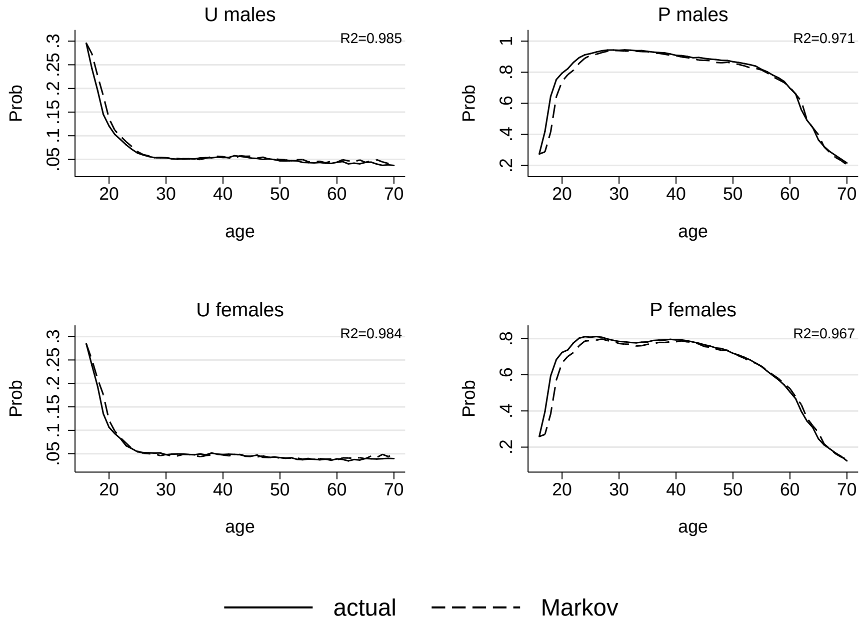
Figure A32: Life-Cycle Profiles of Worker Flows Transitions: Females, No-Child vs Child



Note: Unconditional life-cycle profiles estimated via weighted OLS.

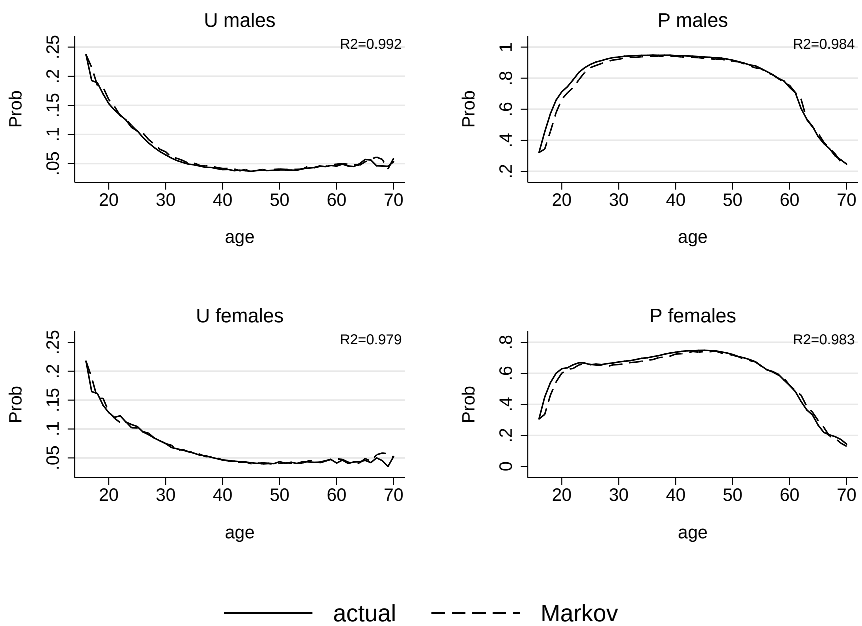
A.3.2 Markovian Simulations by Marital Status and Gender

Figure A33: Markov-Chain Simulated Unemployment and Participation: No-Child



Note: Unconditional life-cycle profiles estimated via weighted OLS.

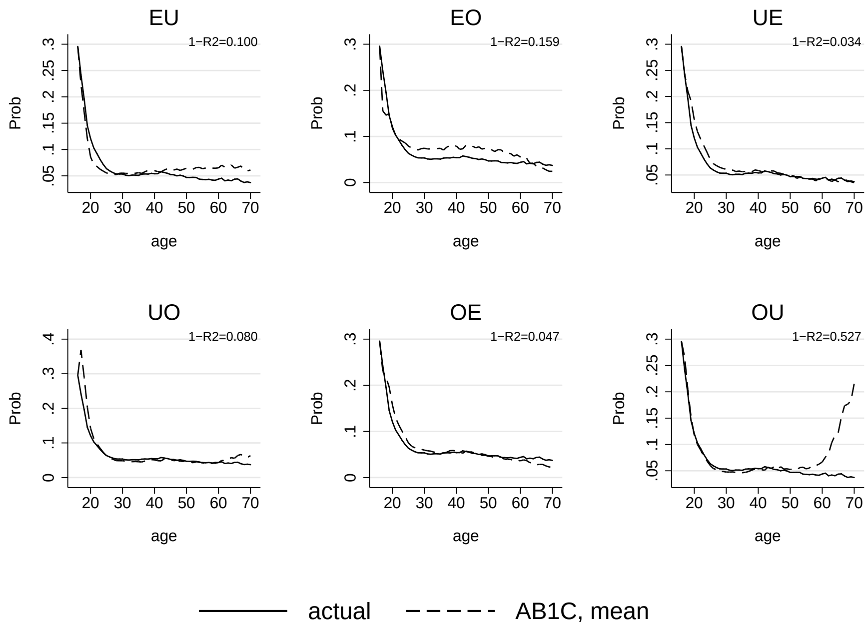
Figure A34: Markov-Chain Simulated Unemployment and Participation: Child



Note: Unconditional life-cycle profiles estimated via weighted OLS.

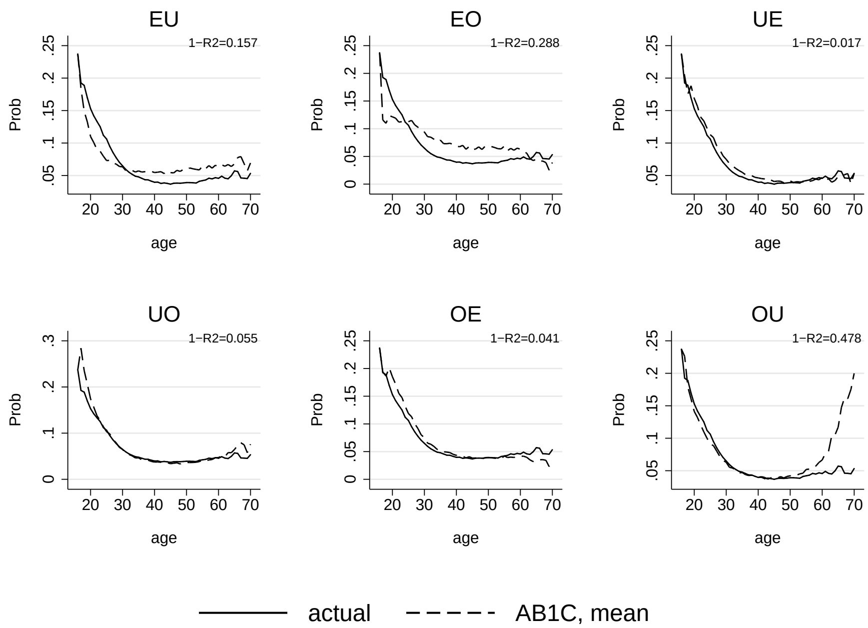
A.3.3 Importance Decomposition of Flows by Child Status and Gender

Figure A35: AB1C Decomposition of the Importance of Flows: Unemployment, Males, No-Child



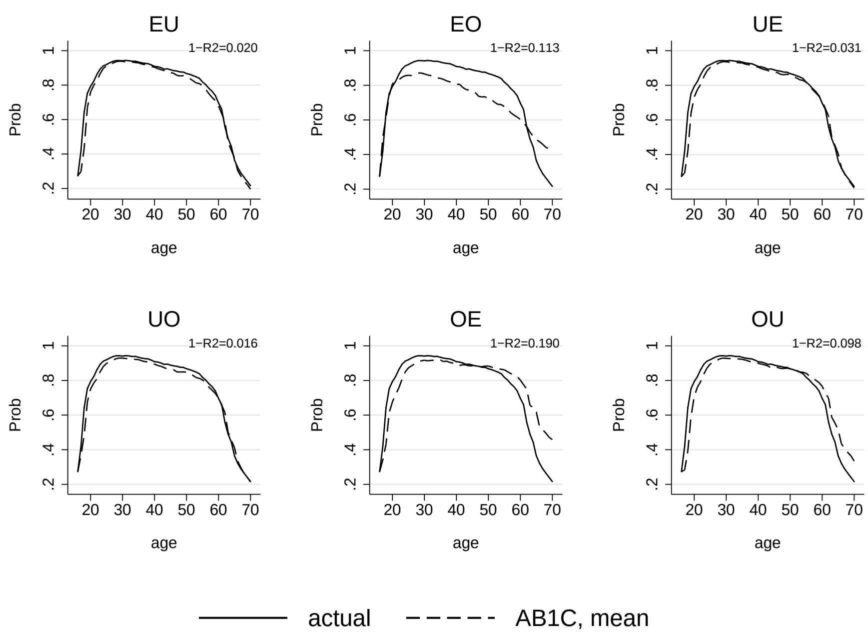
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A36: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Child



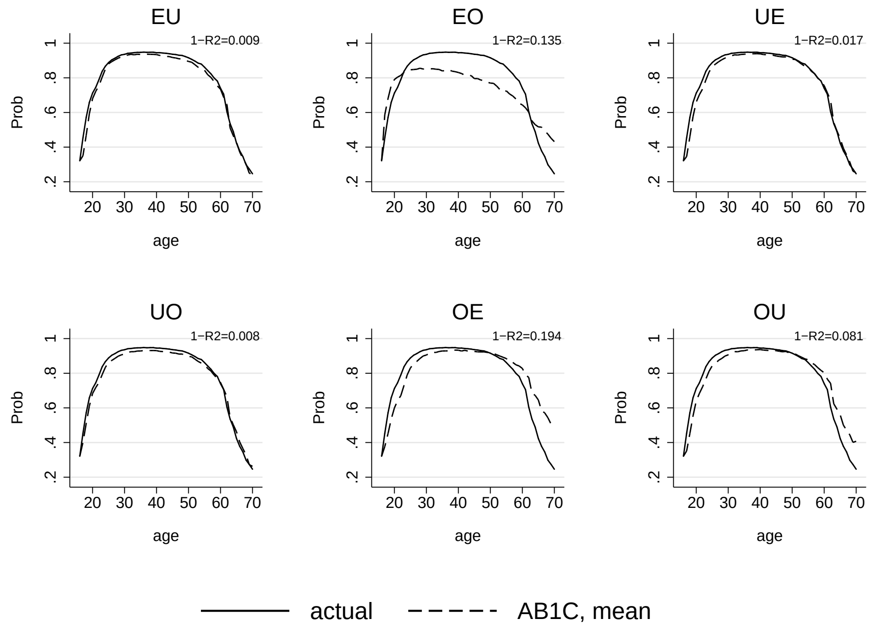
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A37: AB1C Decomposition of the Importance of Flows: Participation, Males, No-Child



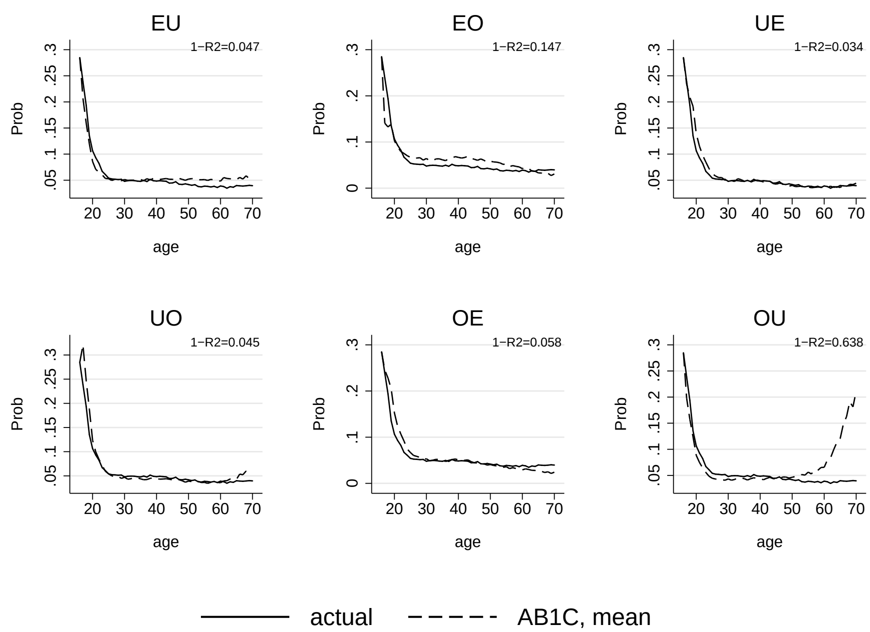
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A38: AB1C Decomposition of the Importance of Flows: Participation, Males, Child



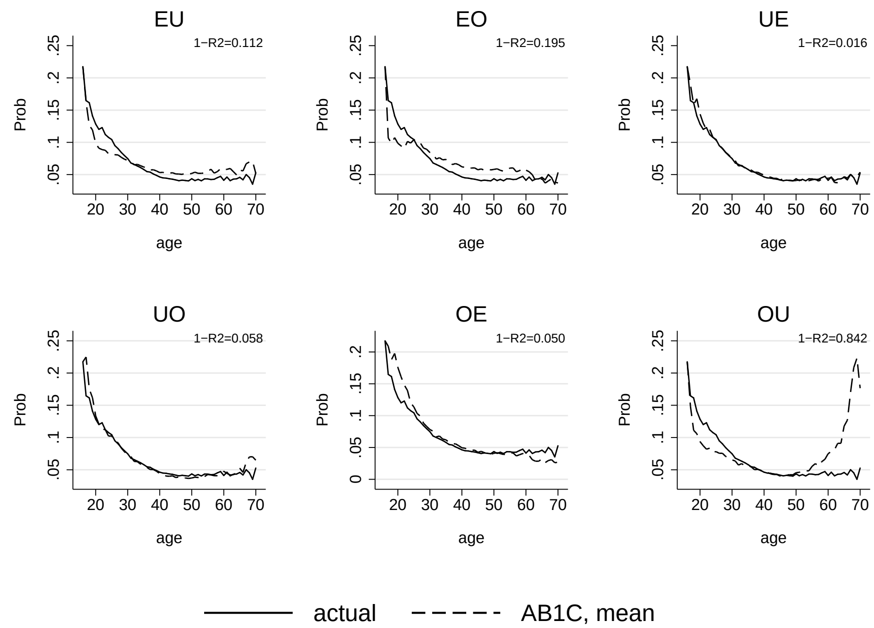
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A39: AB1C Decomposition of the Importance of Flows: Unemployment, Females, No-Child



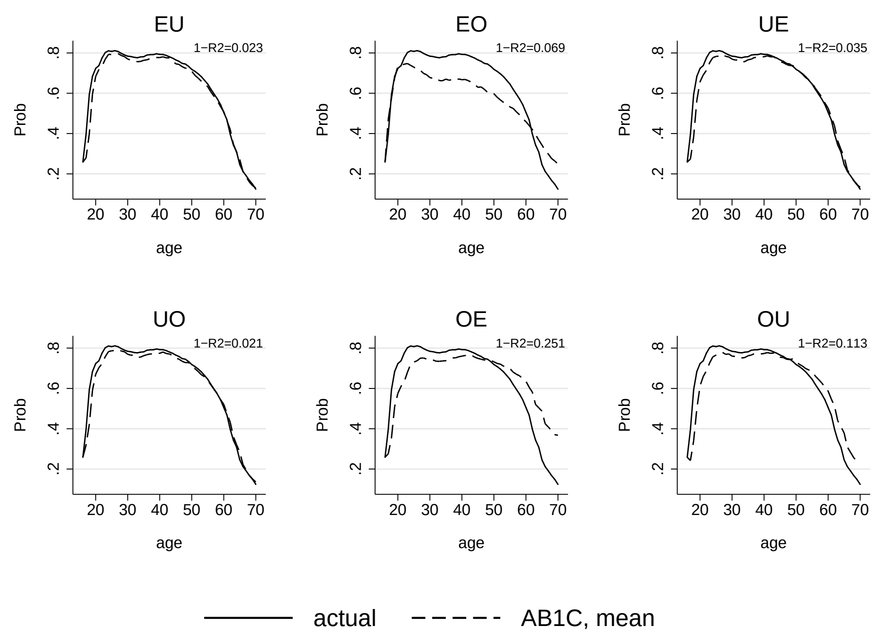
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A40: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Child



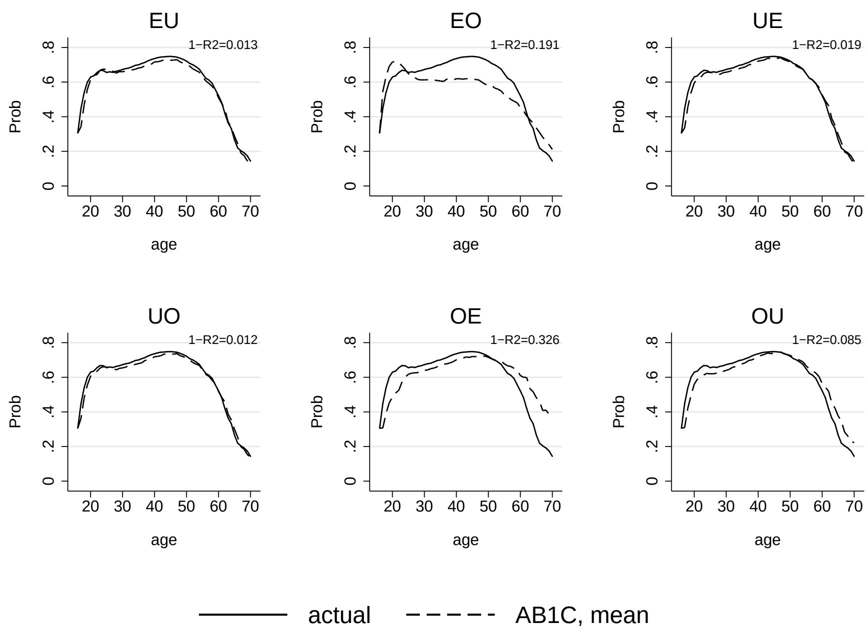
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A41: AB1C Decomposition of the Importance of Flows: Participation, Females, No-Child



Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A42: AB1C Decomposition of the Importance of Flows: Participation, Females, Child



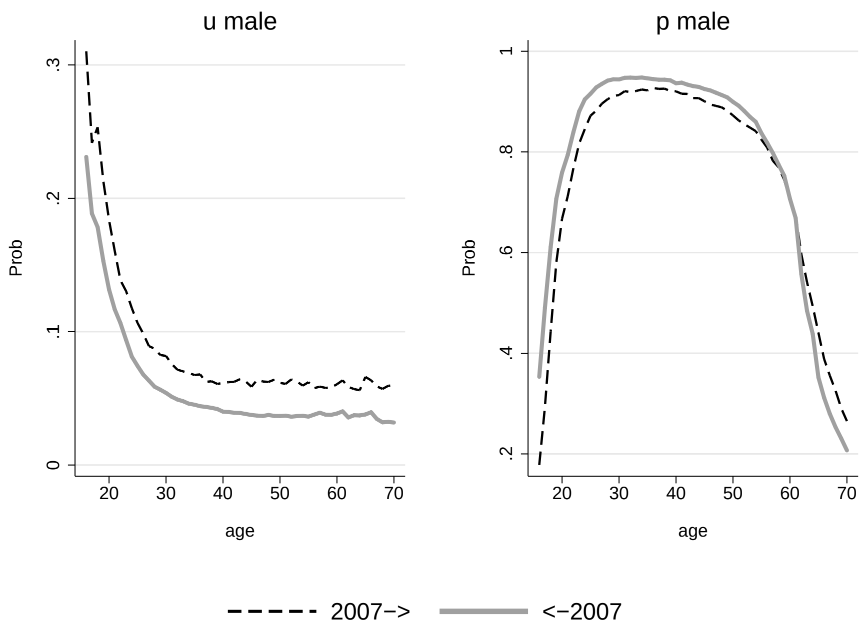
Note: Unconditional life-cycle profiles estimated via weighted OLS.

B Effects of the Great Recession

In this Section, we show in greater detail results for the analysis of the Great Recession. To do so, we report results from our analysis for unconditional transition probabilities, unemployment, and participation rates before and after January 2007.

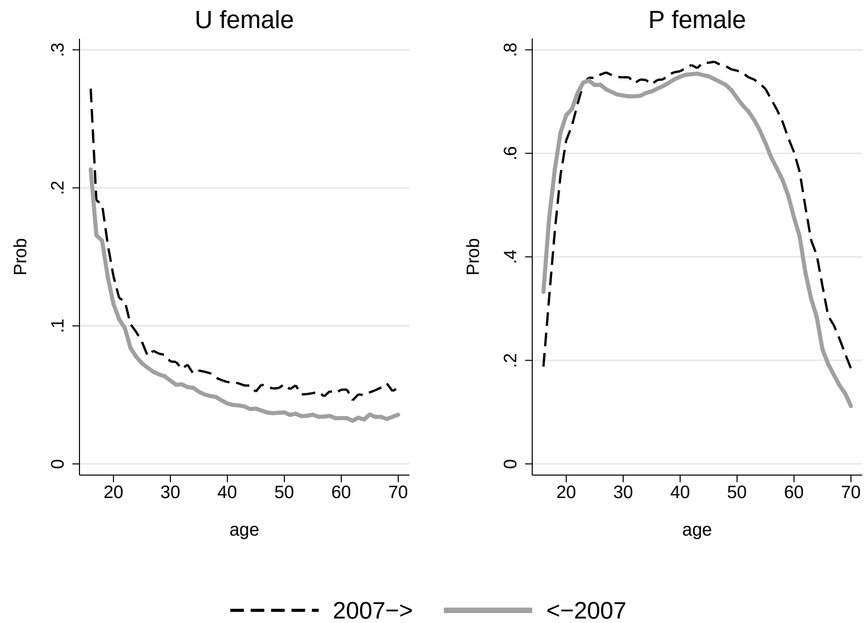
B.1 Estimated Flows and Stocks, Before and After 2007

Figure A43: Life-Cycle Unemployment and Participation Profiles: Males, Before and After 2007



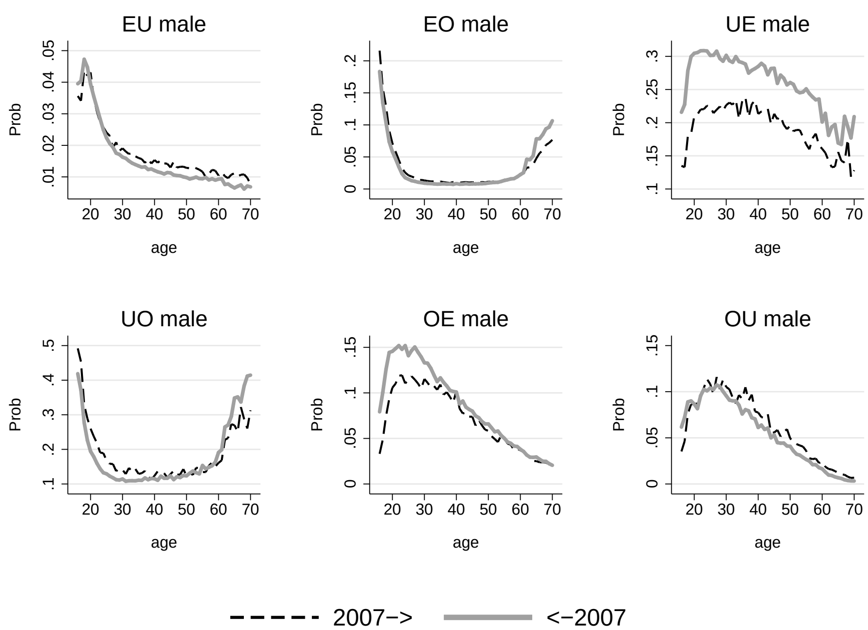
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A44: Life-Cycle Unemployment and Participation Profiles: Females, Before and After 2007



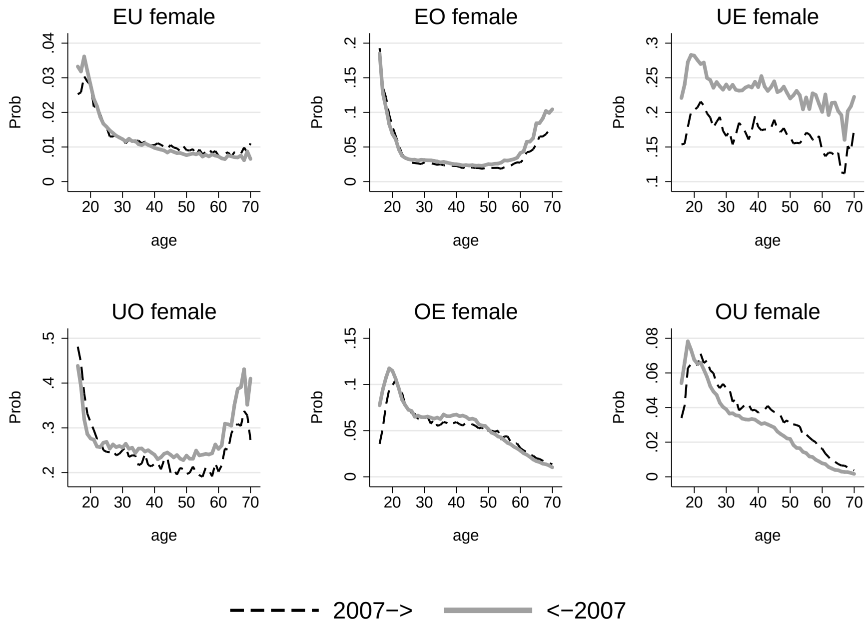
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A45: Life-Cycle Profiles of Worker Flows Transitions: Males, Before and After 2007



Note: Unconditional life-cycle profiles estimated via weighted OLS.

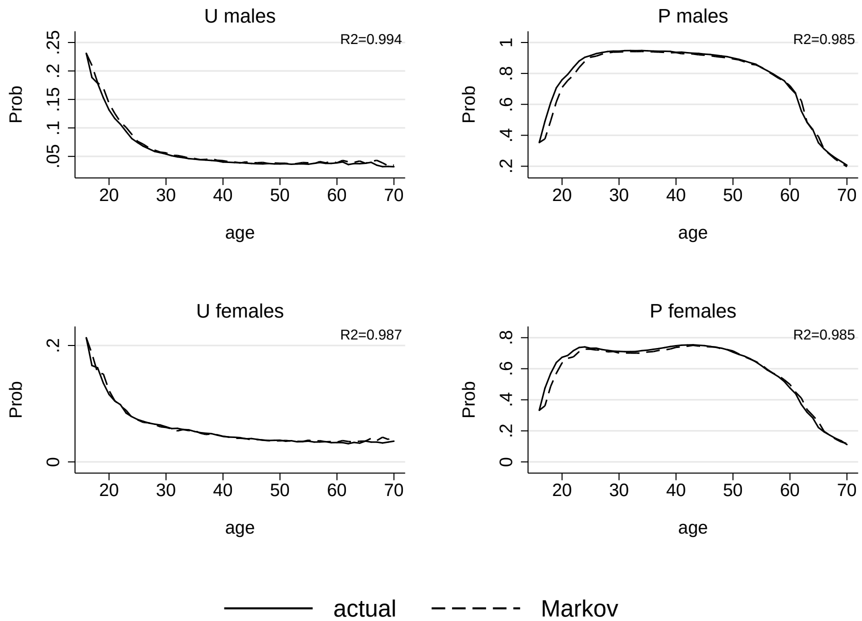
Figure A46: Life-Cycle Profiles of Worker Flows Transitions: Males, Before and After 2007



Note: Unconditional life-cycle profiles estimated via weighted OLS.

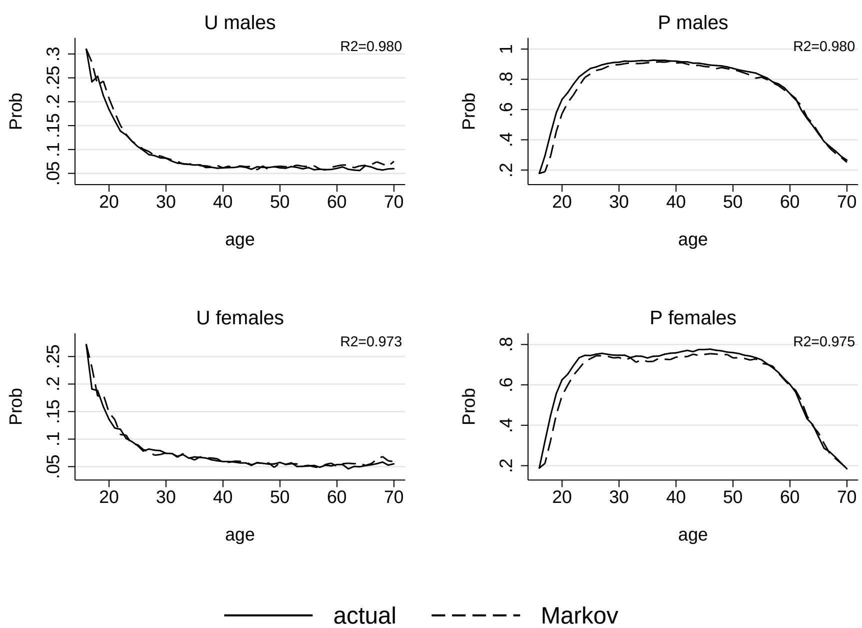
B.2 Markov Chain Analysis

Figure A47: Markov-Chain Simulated Unemployment and Participation: Before 2007



Note: Unconditional life-cycle profiles estimated via weighted OLS.

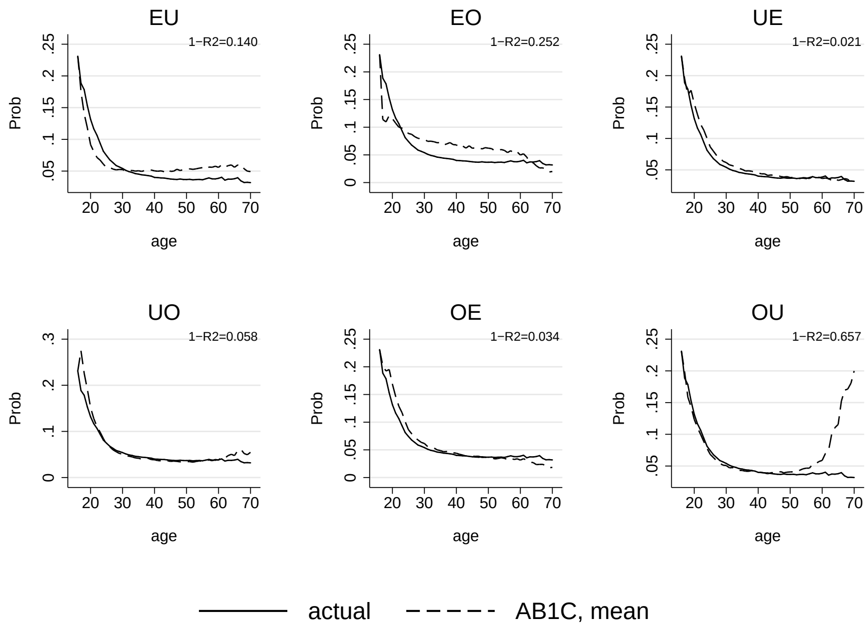
Figure A48: Markov-Chain Simulated Unemployment and Participation: After 2007



Note: Unconditional life-cycle profiles estimated via weighted OLS.

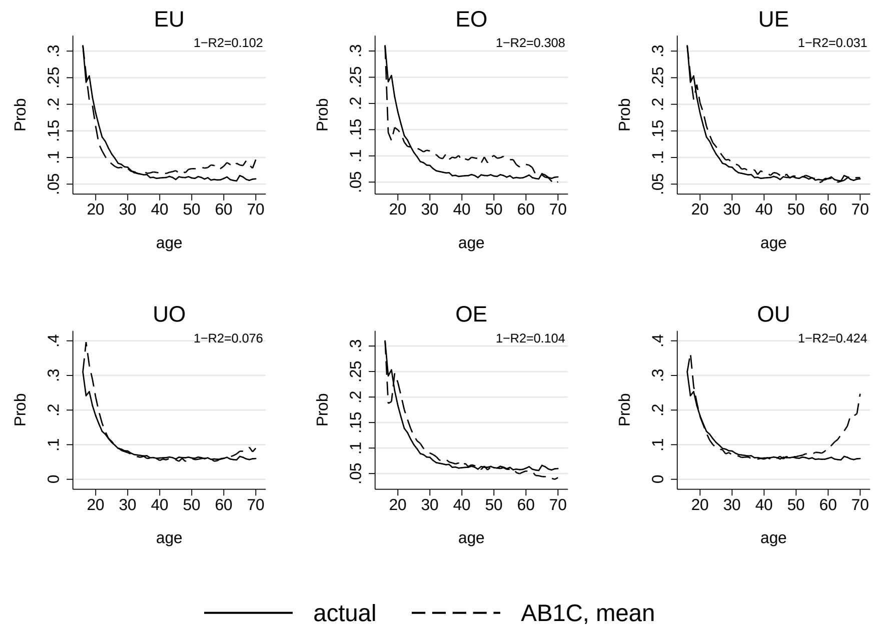
B.3 Importance decomposition of Flows, before and after 2007

Figure A49: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Before 2007



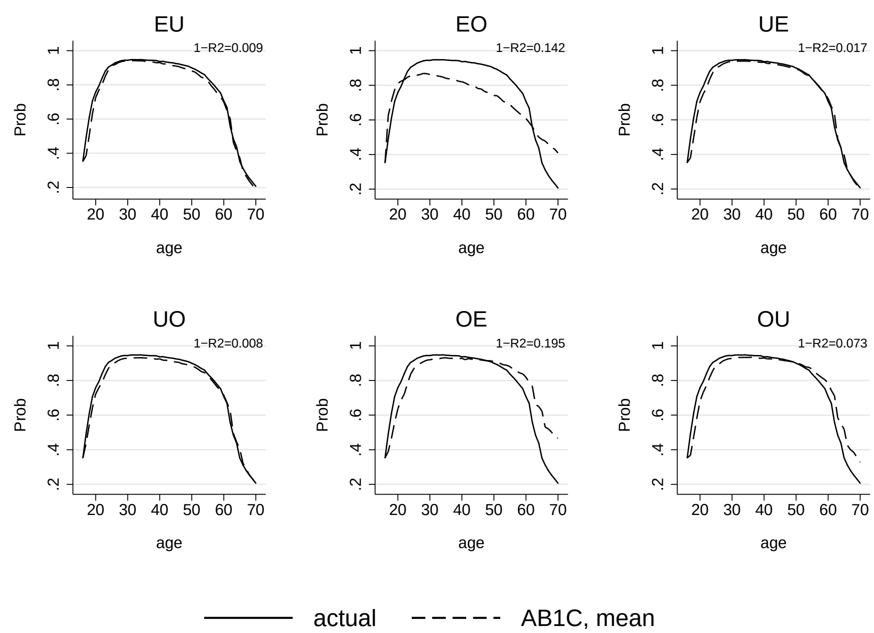
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A50: AB1C Decomposition of the Importance of Flows: Unemployment, Males, After 2007



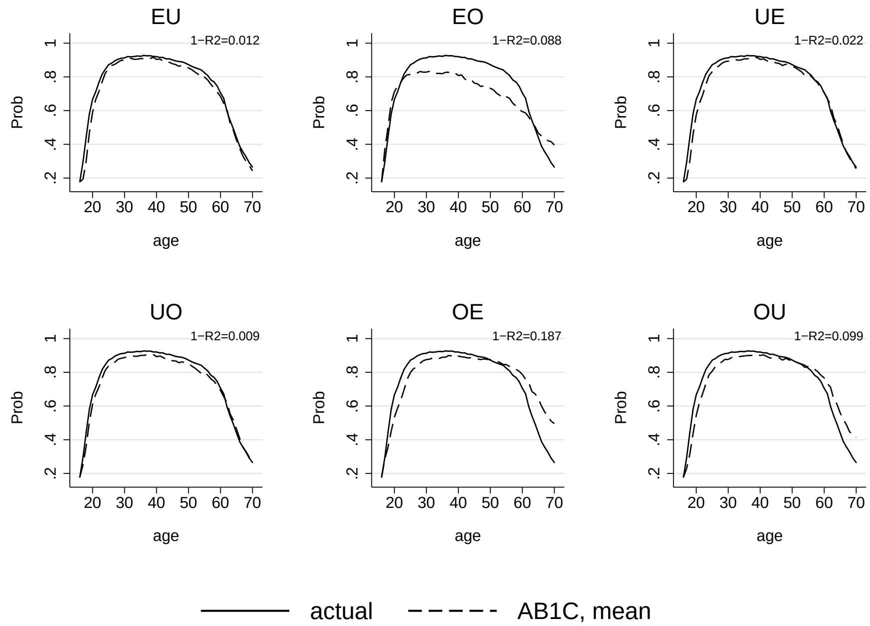
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A51: AB1C Decomposition of the Importance of Flows: Participation, Males, Before 2007



Note: Unconditional life-cycle profiles estimated via weighted OLS.

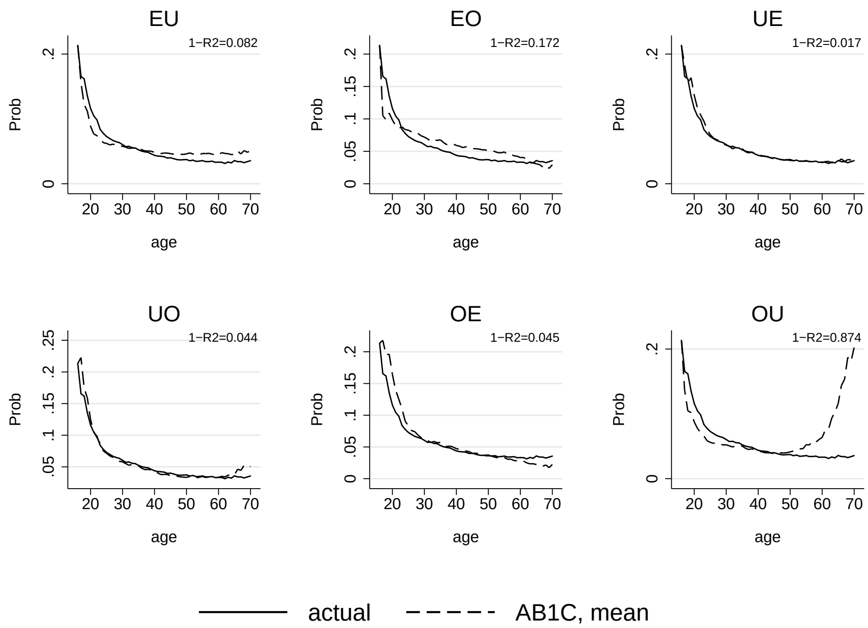
Figure A52: AB1C Decomposition of the Importance of Flows: Participation, Males, After 2007



Note: Unconditional life-cycle profiles estimated via weighted OLS.

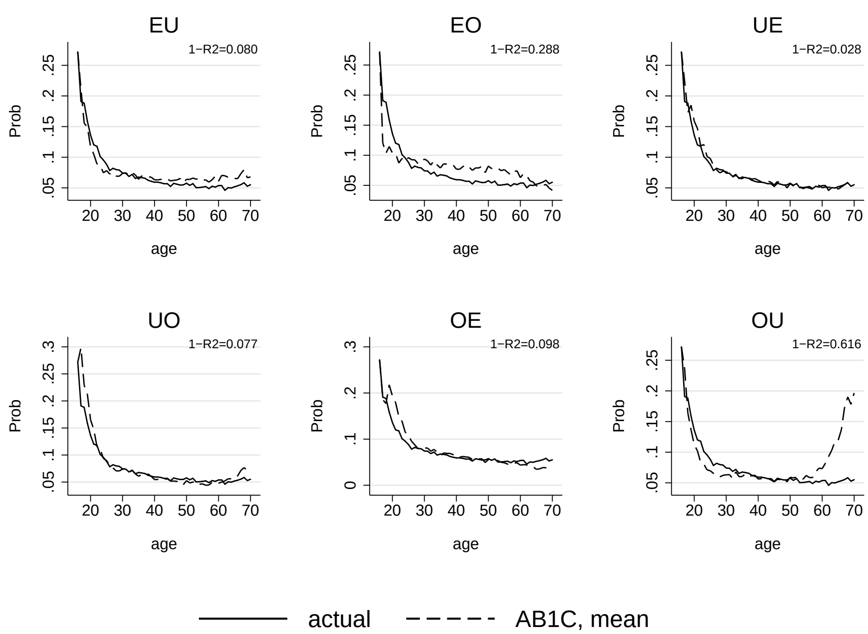
B.4 Role of Inactivity, Before and After 2007

Figure A53: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Before 2007



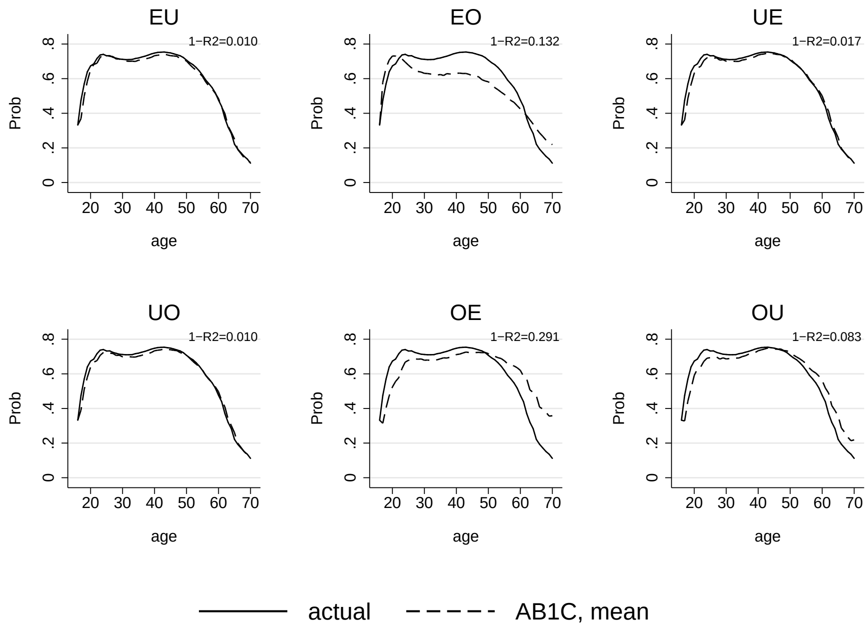
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A54: AB1C Decomposition of the Importance of Flows: Unemployment, Females, After 2007



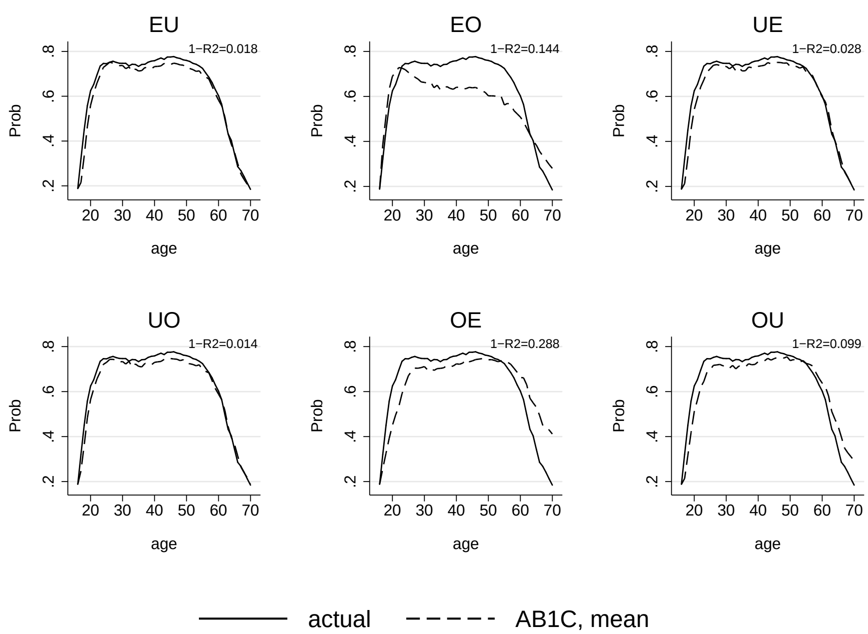
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A55: AB1C Decomposition of the Importance of Flows: Participation, Females, Before 2007



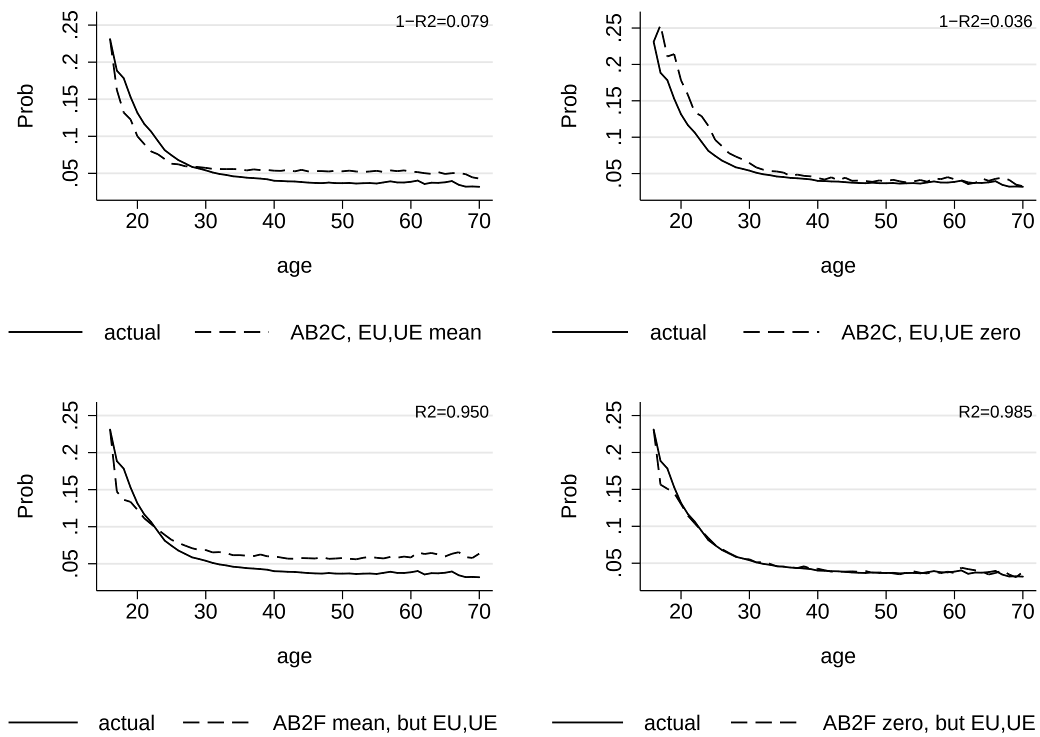
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A56: AB1C Decomposition of the Importance of Flows: Participation, Females, After 2007



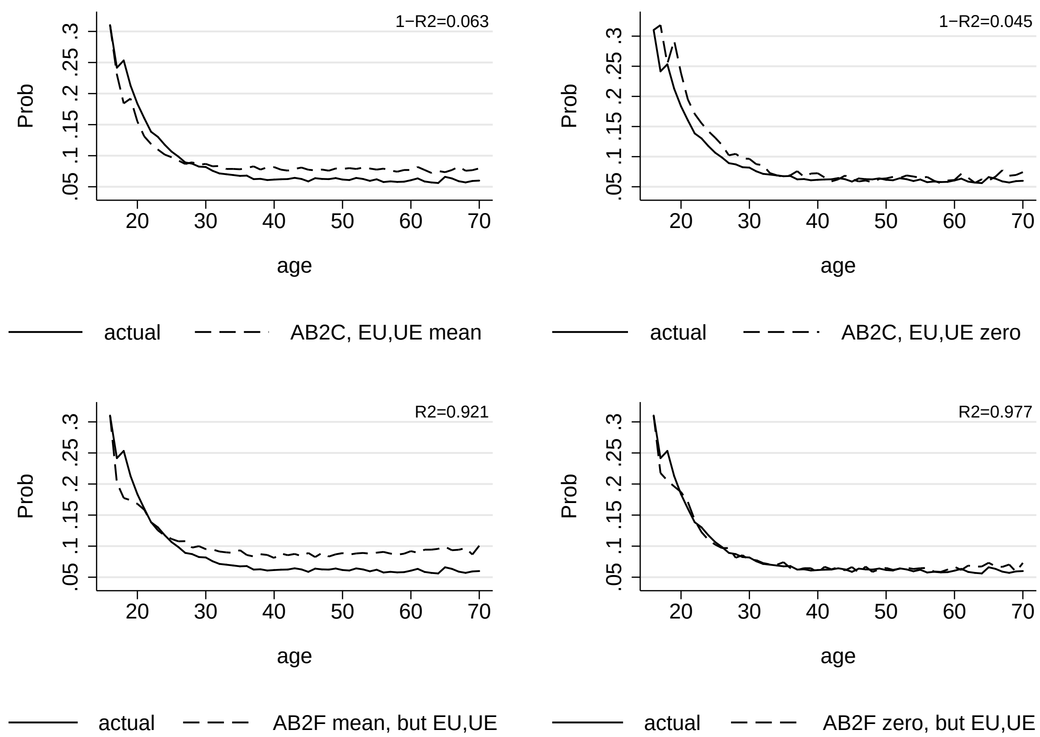
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A57: AB2 Decomposition Neglecting Inactivity for Life-Cycle Unemployment Rates: Males, Before 2007



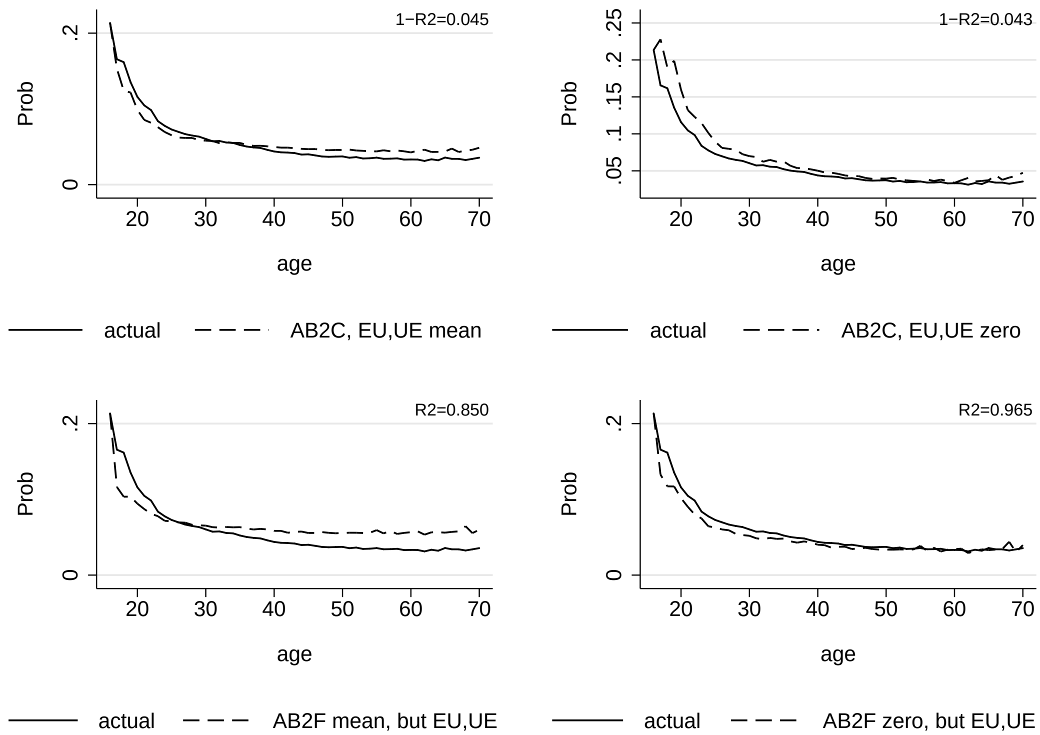
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A58: AB2 Decomposition Neglecting Inactivity for Life-Cycle Unemployment Rates: Males, After 2007



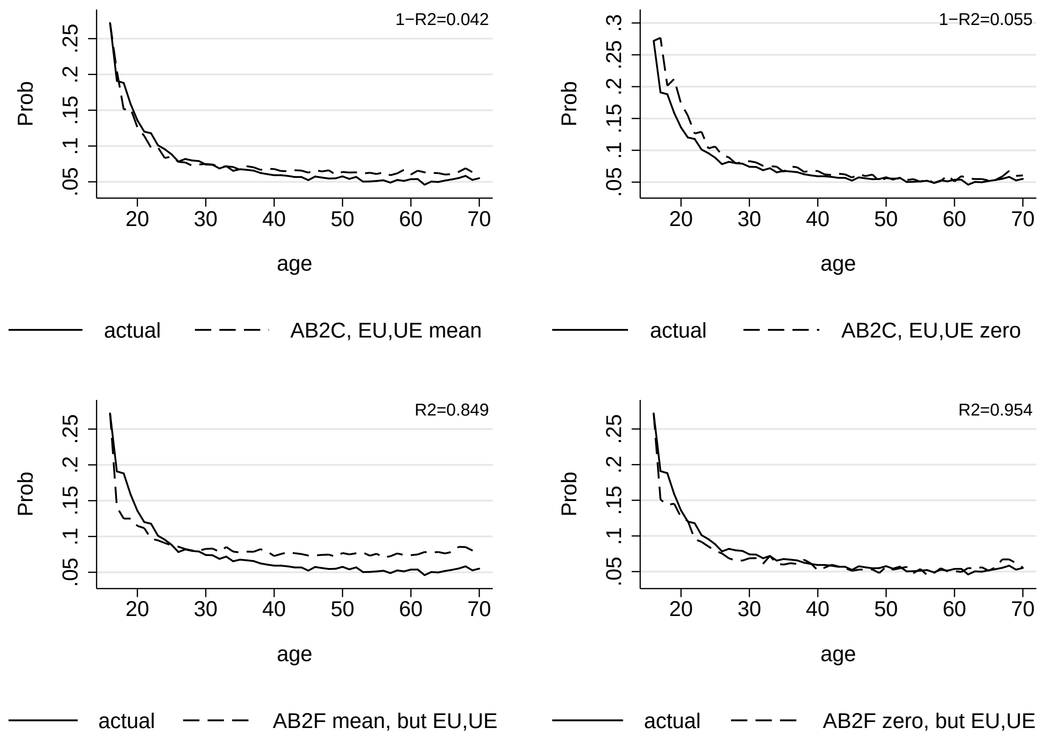
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A59: AB2 Decomposition Neglecting Inactivity for Life-Cycle Unemployment Rates: Females, Before 2007



Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A60: AB2 Decomposition Neglecting Inactivity for Life-Cycle Unemployment Rates: Females, After 2007

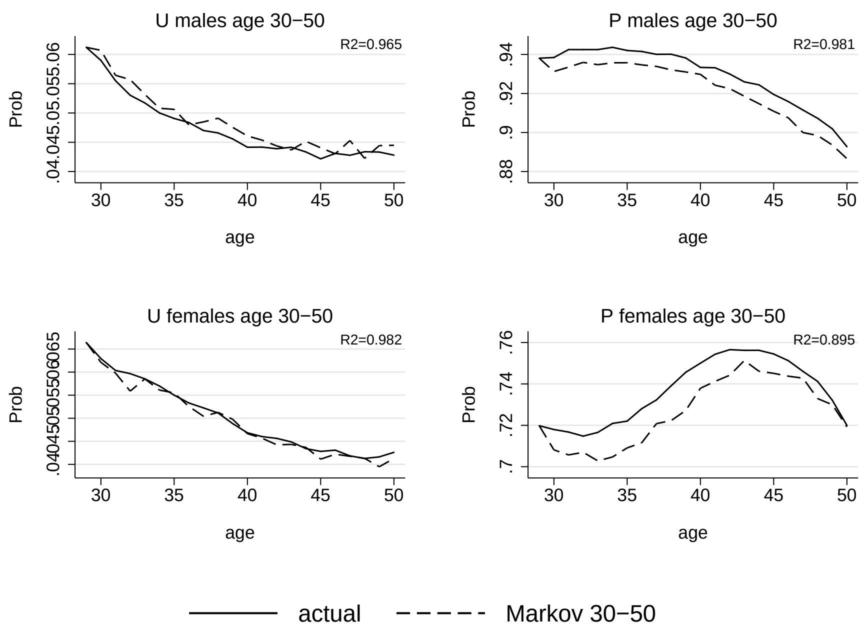


Note: Unconditional life-cycle profiles estimated via weighted OLS.

C Results for Ages 30 to 50

In this section, we present results restricted for individuals between 30 and 50 years old. Since the common wisdom seems to be that inactivity matters mostly for younger and older individuals, restricting our analysis to this population shows how robust our findings are. The fact that annual probability transitions are close to limit ones (due to large transition probabilities, see section D, a priori one expect that our results for ages 30-50 to be hardly different from those covering the baseline range (ages 16-70). Figure A61 shows the results of simulating the unemployment profile for ages 30 to 50, which gives us comparable accuracy to our baseline results. The results for participation are slightly less successful.

Figure A61: Markov-Chain Simulated Unemployment and Participation: Age 30-50



Note: Unconditional life-cycle profiles estimated via weighted OLS.

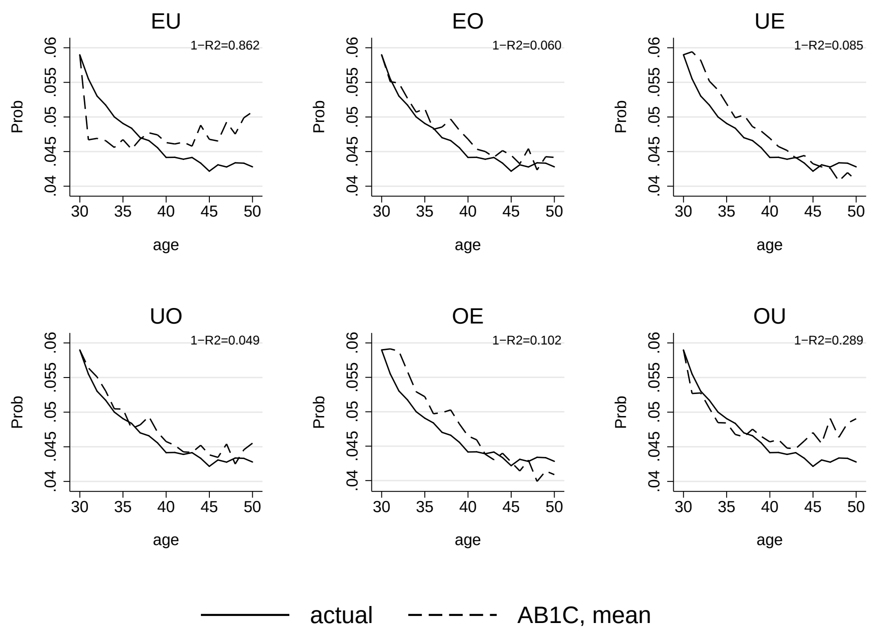
C.1 Decomposition Exercises, Ages 30 to 50

Below we perform the AB1C decomposition for the range 30 to 50. Figures 21 and 22 show the results. In line with our previous analysis for the whole age range, the separation probability (EU) is the most important factor for males, while the OU probability is still important, especially for workers over 40. In contrast, the job finding probability does not affect the male profile by much. For females, the most important flow is OU, seconded by the EU and EO probabilities. Hence, although the importance of inactivity related flows decays in the prime-age group, they are still important for shaping unemployment profiles. The belief that inactivity flows only matter for younger and older workers is not supported by this evidence.

Figures A64 and A65 show the impact of each particular flow on the participation rate over ages 30 to 50. For males, the most important flow is the OE, while for females, both EO and OE are important to explain the profiles.

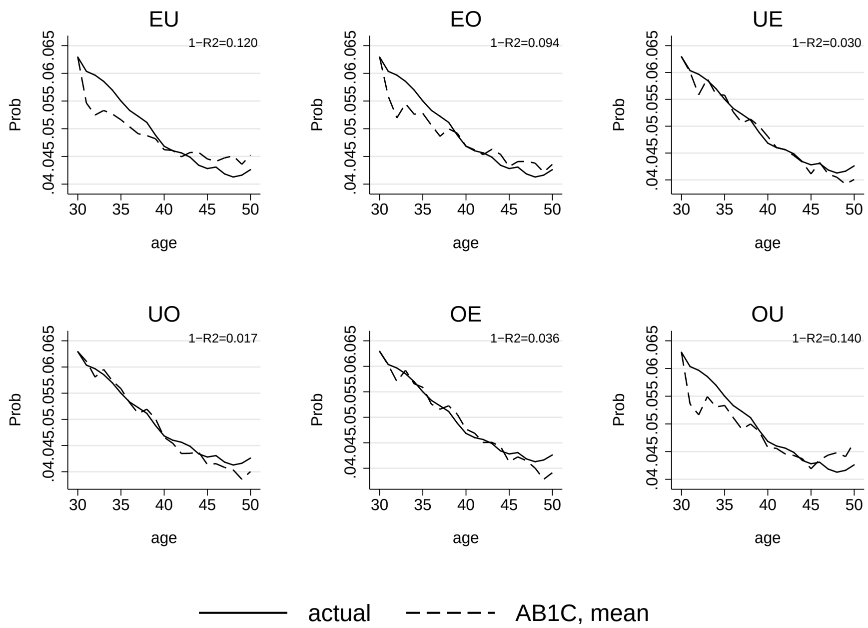
In sum, while the importance of inactivity related flows is decreased for prime-aged workers, flows in and out of inactivity still have a substantial influence on unemployment and participation over the life cycle for this group.

Figure A62: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Age 30-50



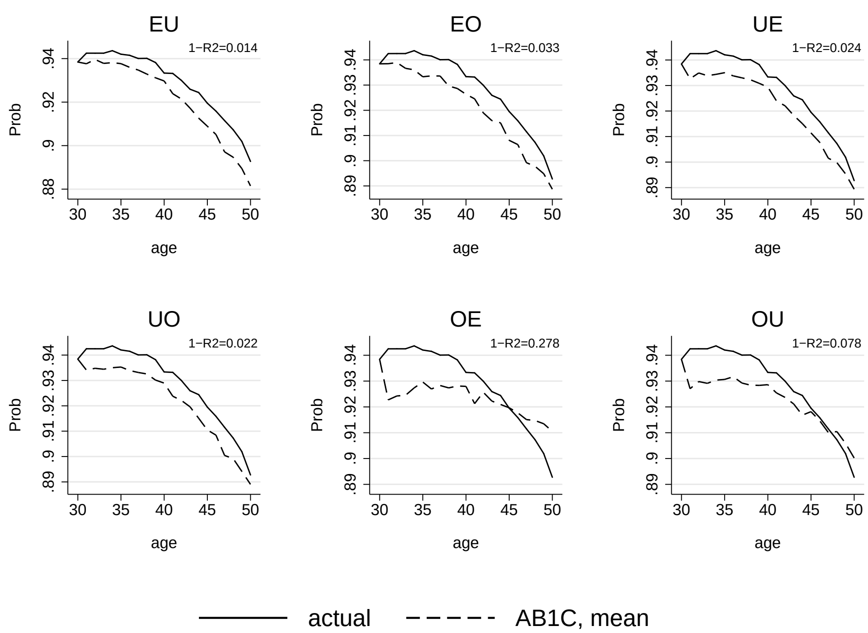
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A63: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Age 30-50



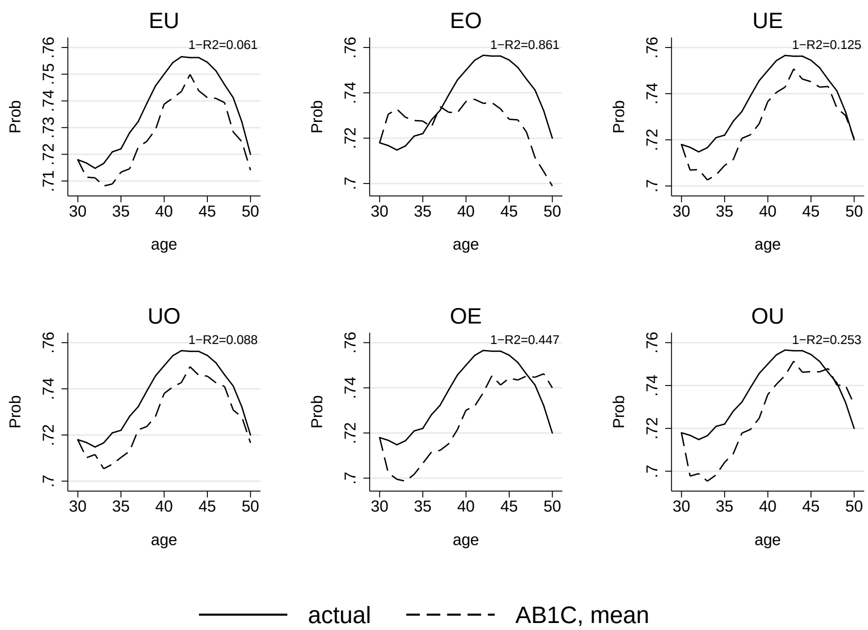
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A64: AB1C Decomposition of the Importance of Flows: Participation, Males, Age 30-50



Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A65: AB1C Decomposition of the Importance of Flows: Participation, Females, Age 30-50



Note: Unconditional life-cycle profiles estimated via weighted OLS.

D Alternative Decomposition Methods

Our decomposition method is similar to the one used by Pissarides (1986) and Shimer (2012). More specifically, unemployment and labour force participation approximations in the latter are the result of iterating the Markov chains an infinite number of times. Labour states obtained from twelve months of transitions (to simulate one year in the life of a worker) with empirical transition probabilities are not very different from the Markov chain limit. In most cases, the approximation is accurate so that we can construct theoretical counterparts to the observed proportion of individuals in each of the three considered states $\{e, u, o\}$ at age a using the Markov chain limit. Therefore, the approximation at any age a can be constructed by solving the following linear system[1]

$$\begin{aligned}
(EU_a + EO_a)\,\widetilde{E}_a &= UE_a\widetilde{U}_a + OE_a\widetilde{O}_a \\
(UE_a + UO_a)\,\widetilde{U}_a &= EU_a\widetilde{E}_a + OU_a\widetilde{O}_a \\
(OE_a + OU_a)\,\widetilde{O}_a &= EO_a\widetilde{E}_a + UO_a\widetilde{U}_a
\end{aligned}$$

The interpretation of these equations is straightforward. The left hand side of these equations represent the flow of individuals transiting away from states $\{e, u, o\}$ respectively, at the end of age a. The right hand side accounts for the number of individuals transiting into those same states. These two numbers must be the same, assuming a stationary age-specific population structure and stationary transition probabilities xz_a. Solving for the states, we get functional forms that relate them to age specific transition rates only.

$$\begin{aligned}
\widetilde{E}_a &= \widetilde{E}(UE_a, UO_a, OE_a, OU_a) \\
\widetilde{U}_a &= \widetilde{U}(EU_a, EO_a, OE_a, OU_a) \\
\widetilde{O}_a &= \widetilde{O}(EU_a, EO_a, UE_a, UO_a)
\end{aligned}$$

accordingly, we can construct these "theoretical" counterparts for participation ($\widetilde{p}_a = 1 - \widetilde{O}_a$) and unemployment rates ($\widetilde{u}_a = \widetilde{U}_a/(\widetilde{E}_a + \widetilde{U}_a)$) using the above equations and our estimates of $\{XZ_a\}$:

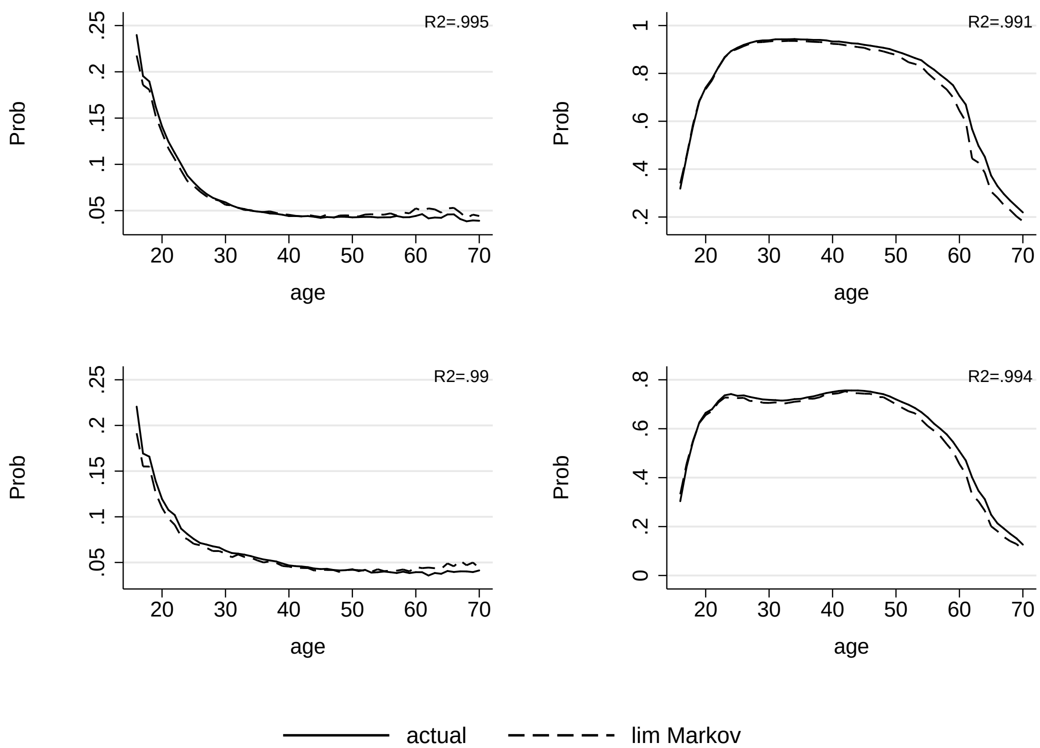
$$u_a \approx \widetilde{u}_a = \frac{\widetilde{U}_a}{\widetilde{U}_a + \widetilde{E}_a} = \frac{OE_aEU_a + OU_a(EU_a + EO_a)}{OE_a(UO_a + EU_a) + UE_a(OE_a + OU_a) + OU_a(EU_a + EO_a)}$$

$$\begin{aligned}
p_a &\approx \widetilde{p}_a \\
&= 1 - \widetilde{O}_a = \frac{UE_a(OE_a + OU_a) + OE_a(UO_a + EU_a) + OU_a(EU_a + EO_a)}{UE_aEO_a + EO_aUO_a + UO_aEU_a + UE_a(OE_a + OU_a) + OE_a(UO_a + EU_a) + OU_a(EU_a + EO_a)}
\end{aligned}$$

In Figure A66 we plot the observed versus theoretical (constructed) rates, for both men and women. As seen from the Figure, the theoretical rates follow closely their observed counterparts and pose a reasonable approximation to the observed profiles. Notice that in order to calculate stocks

[1] The limiting labour states e, u, o are just the normalized eigenvector (so that its components add up to 1) associated to an eigenvalue of value 1.

Figure A66: Limit Markov-Chain Simulated Unemployment and Participation



Note: Unconditional life-cycle profiles estimated via weighted OLS.

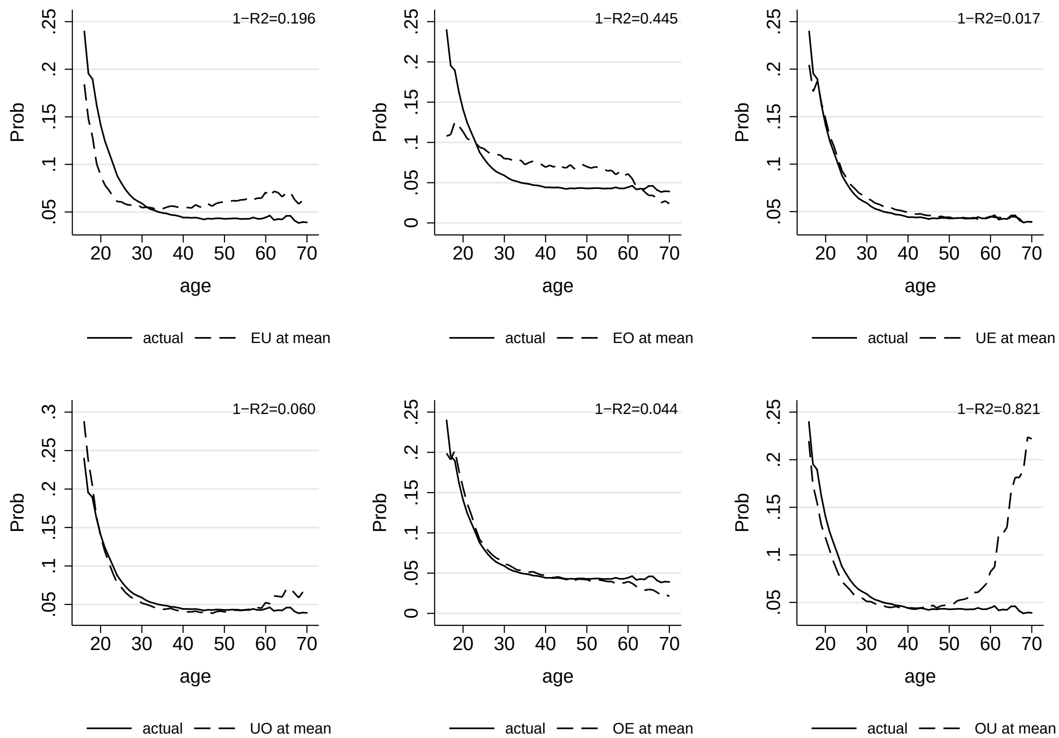
of unemployed, employed and inactive workers, the method above does not rely on initial conditions/distribution of workers across employment states but only age-specific transition probabilities. The goodness of fit of the theoretical rates is due to high monthly transition probabilities, which dwarfs the effect of initial conditions.

Given that theoretical participation and unemployment rates depend only on age-specific transition probabilities, we can assess their relative importance in explaining aggregate life-cycle profiles. Using the same logic as in the "all but one change" (AB1C) method,[2] we compute the limiting states at each age by using our estimates XZ_a. However, we keep fixed a particular transition probability at its mean life-cycle value, one at a time, and we allow the rest of them to change according to age. We present these decompositions for unemployment and participation in Figures A67 to A70 below.

When comparing the results from this "limit" method to the ones we see in the Markov chain analysis, we get roughly identical results. In terms of participation, the most important transition

[2]This is in contrast to what Shimer (2012) does in the context of a business cycle decomposition. He fixes all transition probabilities at their mean and changes only one, what we labeled the AB1F method above.

Figure A67: Limit AB1C Decomposition of the Importance of Flows: Unemployment, Males



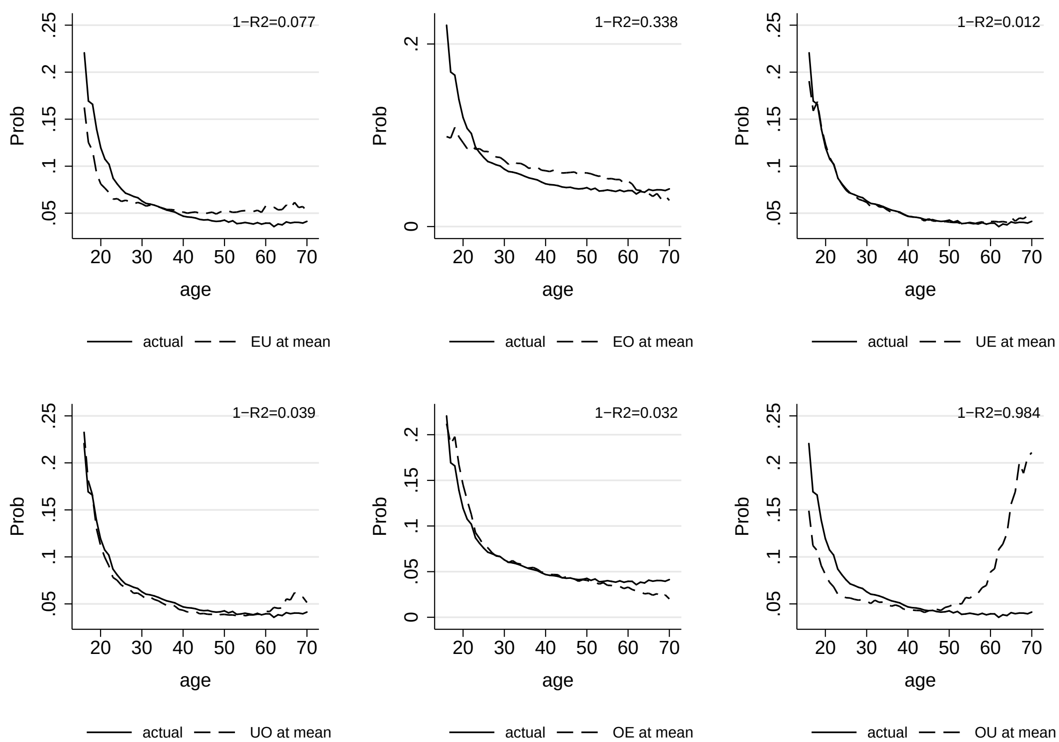
Note: Unconditional life-cycle profiles estimated via weighted OLS.

probability is the one from employment to inactivity EO. If this transition probability were to be constant throughout the life-cycle, the participation profile would be flatter. The EO probability is very important to determine early and late life employment status. Also, movements from inactivity into the labour force (both OE and OU probabilities) determine to a great extent unemployment after the age of 60.

As for the life-cycle profile of the unemployment rate, again the EO probability plays an important role, followed by the EU as well as the OU transition probabilities. The job finding probability (UE) does not affect differences in life-cycle participation and unemployment significantly. It turns out that the transitions into and out from the labour force are quite important in shaping unemployment and participation rates life-cycle profiles.

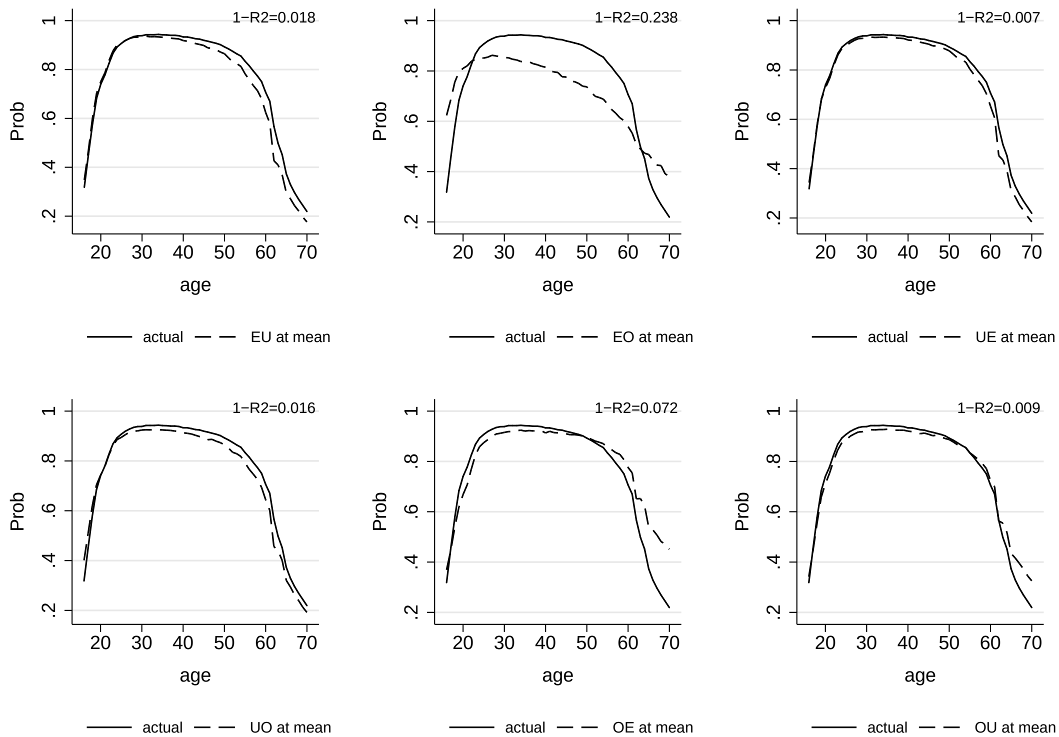
These results contrasts to Shimer (2012) and Fujita and Ramey (2009) findings in relation to the business cycle. These authors show that UE and EU flows are enough to account for the cyclical fluctuations of the unemployment rate. For life-cycle analysis, our evidence shows that inactivity transitions are key to understand the unemployment and participation by age.

Figure A68: Limit AB1C Decomposition of the Importance of Flows: Unemployment, Females



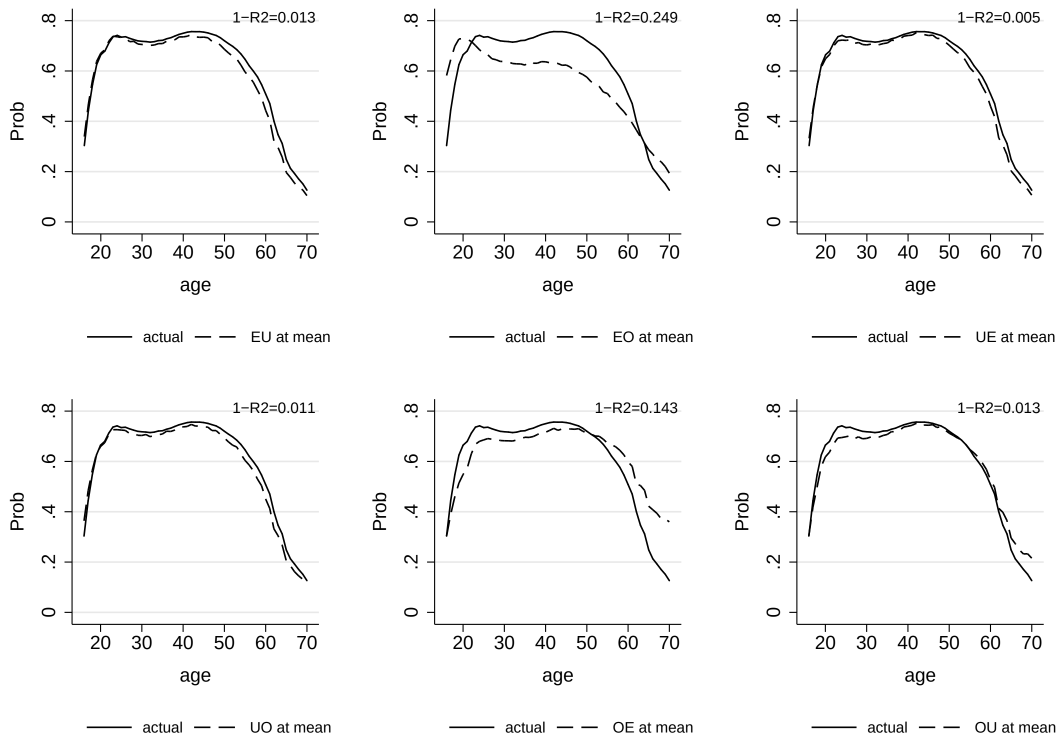
Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A69: Limit AB1C Decomposition of the Importance of Flows: Participation, Males



Note: Unconditional life-cycle profiles estimated via weighted OLS.

Figure A70: Limit AB1C Decomposition of the Importance of Flows: Participation, Females



Note: Unconditional life-cycle profiles estimated via weighted OLS.

E Introducing Controls

In this appendix, we present the same figures as in the body of the paper, but here our estimates include different sets of controls in matrix D below:

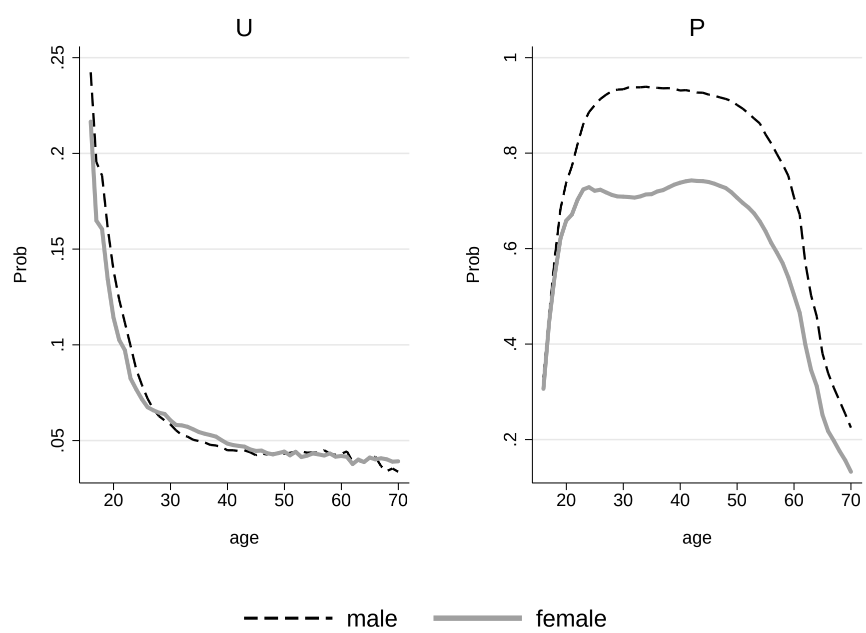
$$f_{atc}^{XZ}\sqrt{N_{atc}^{X}} = \sum_{a=1}^{A} XZ_a D_{atc}\sqrt{N_{atc}^{X}} + \beta W_{atc}\sqrt{N_{atc}^{X}} + \epsilon_{atc}\sqrt{N_{atc}^{X}} \qquad \text{(A1)}$$

When we control for time, cohort and state effects, our conclusions remain as in the main body of the paper. Adding educational attainment dummies to our estimations do not change our results either, as hinted by the exercise in the paper where we separate samples by educational group.

It is important to consider the interaction between cohort and time effects. In particular, we find it crucial for isolating the life-cycle component for the post Great Recession period (2007 onwards). This suggests potentially different effects of the business cycle on different cohorts of the population, possible due to schooling quality or vintage human capital differences across generations. Once we properly take these issues into account, our estimated life-cycle profiles are very similar to the results using unconditional estimates reported in the body of the paper.

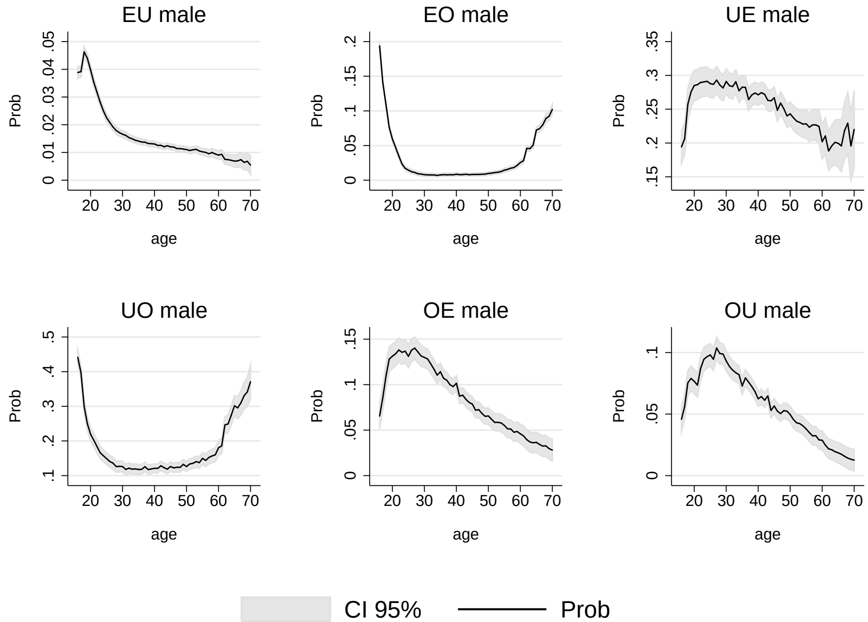
E.1 Controlling for Cohort, Time, and State (CTS)

Figure A71: Life-Cycle Unemployment and Participation Profiles, Control CTS



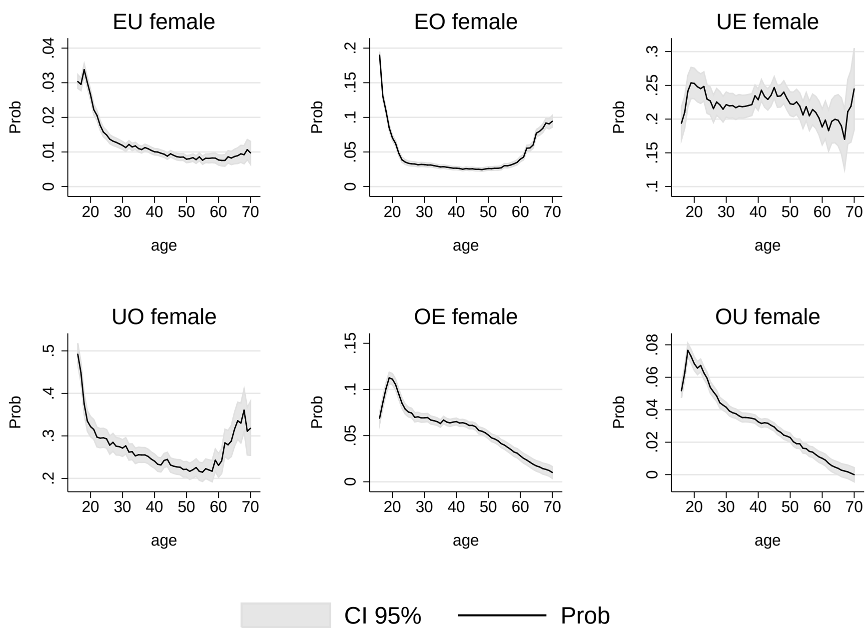
Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

Figure A72: Life-Cycle Profiles of Worker Flows Transitions, Males, Control CTS



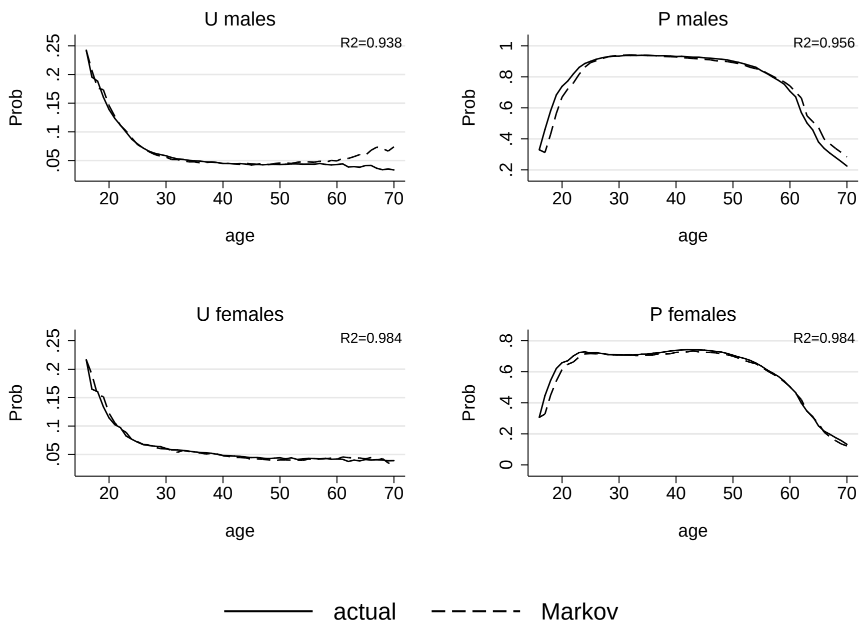
Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

Figure A73: Life-Cycle Profiles of Worker Flows Transitions, Females, Control CTS



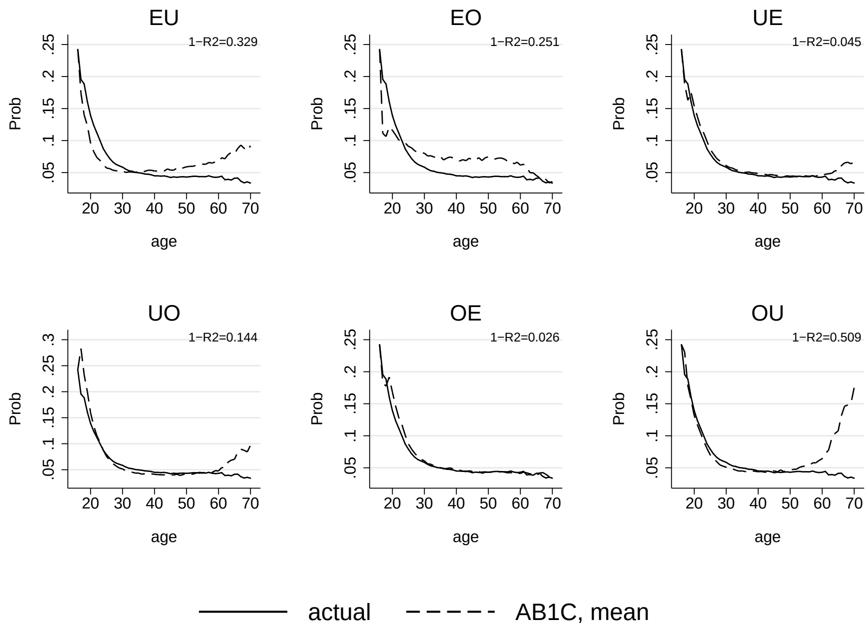
Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

Figure A74: Markov-Chain Simulated Unemployment and Participation, Control CTS



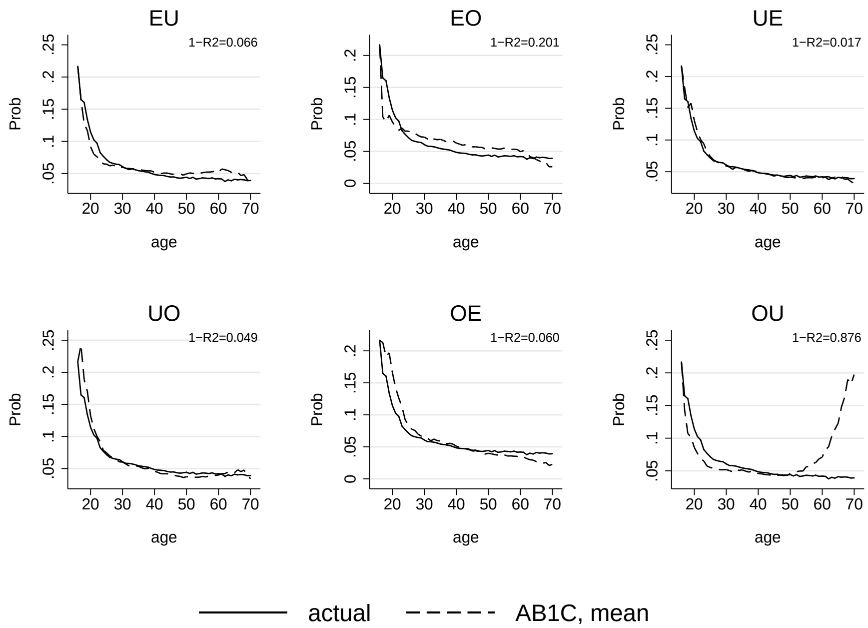
Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

Figure A75: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Control CTS



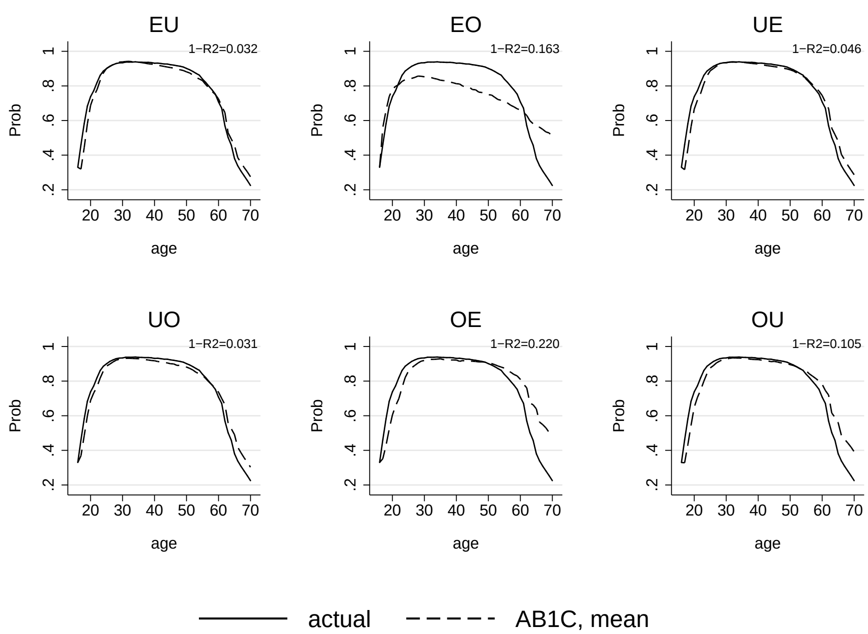
Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

Figure A76: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Control CTS



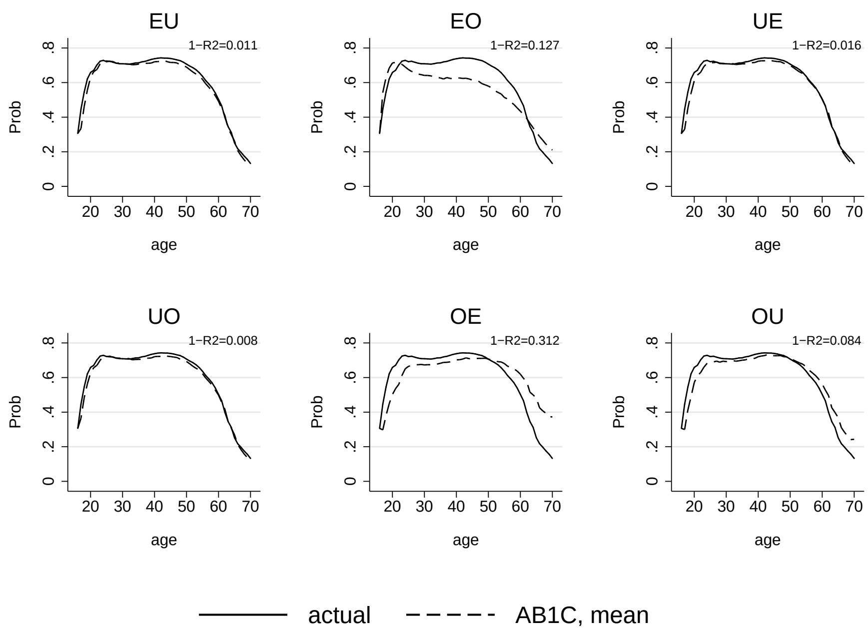
Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

Figure A77: AB1C Decomposition of the Importance of Flows: Participation, Males, Control CTS



Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

Figure A78: AB1C Decomposition of the Importance of Flows: Participation, Females, Control CTS



Note: Life-cycle profiles controlled for 5-year cohort effects, 4th-order polynominal cohort-specific time trends, seasonal monthly dummies, and state effects, estimated via weighted OLS.

F Time-Aggregation Results

F.1 Method

Following Shimer (2013) and Elsby, Hobijn, and Şahin (2013), we perform a simple transformation for each one of matrices Γ_i, which contain monthly transition probabilities between labour market states for each age i. As shown by Shimer (2013), if all eigenvalues of Γ_i are real, positive and distinct (as is the case for each considered age in our data), then matrix $\widetilde{\Gamma}_i$, containing the instantaneous transition rates between each labour market state, can be recovered by a simple eigenvalue/eigenvector transformation: $\widetilde{\Gamma}_i = P_i \widetilde{\Lambda}_i P_i^{-1}$, where P_i is the matrix of eigenvectors of matrix Γ_i; Λ_i is the diagonal matrix with eigenvalues of Γ_i; finally, $\widetilde{\Lambda}_i$ is the same as Λ_i, but its elements are replaced by natural logarithms of the original eigenvalues in Λ_i. Finally, we use transition probabilities instead of transition rates, by computing $\widetilde{XZ} = 1 - \exp(-f_{XZ})$ where f_{XZ} is element (X, Z) of matrix $\widetilde{\Gamma}_i$. We report monthly time-aggregation corrected transition probabilities in Figures A79 to A80.

F.2 Robustness of AB1C method:

Given the eigenvalues Λ_i and the relationship between instantaneous and discrete time transition probabilities, we can construct transition probabilities for any arbitrary length of time: instead of month-to-month transitions, we can compute transitions for weeks, days, hours, etc. Note that the monthly transition probability between states j and k is given by

$$\widetilde{XZ} = 1 - \exp(-f_{XZ}\Delta t)$$

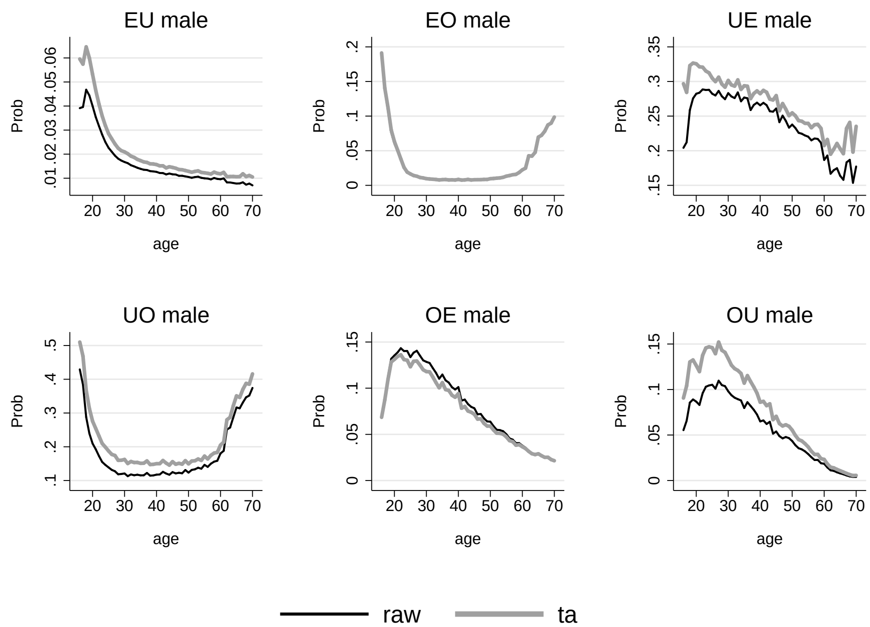
where $\Delta t = 1$ represents one month. Thus, to obtain a weekly, daily or hourly transition probability, we just have to make $\Delta t = 7/30$, $\Delta t = 1/30$ or $\Delta t = 1/(24 * 30)$ respectively. We report the AB1C decomposition for monthly adjusted transition probabilities in Figures A86 to A85. The corrected transition probabilities are used to simulate the life-cycle profiles of Unemployment and Participation of a cohort. While some corrected flows are very different from the unadjusted ones, the Markovian process accurately predicts stocks of labour statuses only using flows (see Figure A81).

As we shorten the frequency of transitions, the resulting transition probability matrices (for example, one per every hour of a 55 year life-cycle in the case of hourly transitions between 16 and 70 years of age) become almost diagonal, since the probability of transiting out of the current labour force status during the next hour is close to zero. Thus, performing our AB1C decomposition on these higher frequency transitions gives us an almost ceteris paribus decomposition exercise: since the relative perturbation to diagonal elements of the matrix when replacing some off-diagonal and age-specific transition probability with its life-cycle mean becomes minimal. These results are shown in figures A86 to A89 for the hourly case.

Finally, we replicate the AB2 decompositions to understand the effects of omitting inactivity in the unemployment and participation life-cycle profiles. Using both monthly and hourly time-aggregation corrected probabilities, we obtain very similar results to those of Section 5 in the main text. We show the robustness of the AB1C decomposition and confirm the results in the main body of the paper.

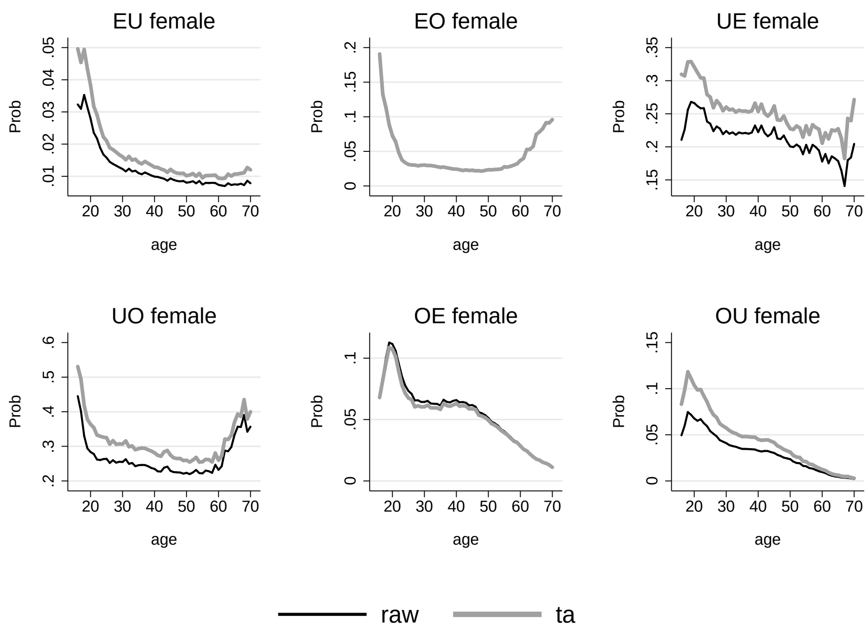
F.3 Monthly Corrected Flows and Simulations

Figure A79: Life-Cycle Profiles of Worker Flows Transitions: Males, Corrected for Time-Aggregation



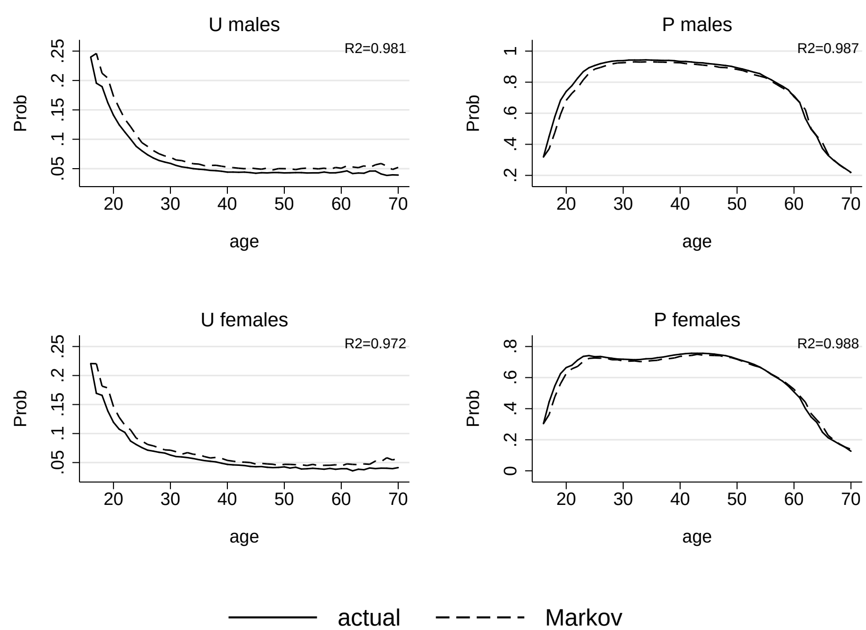
Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A80: Life-Cycle Profiles of Worker Flows Transitions: Females, Corrected for Time-Aggregation



Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

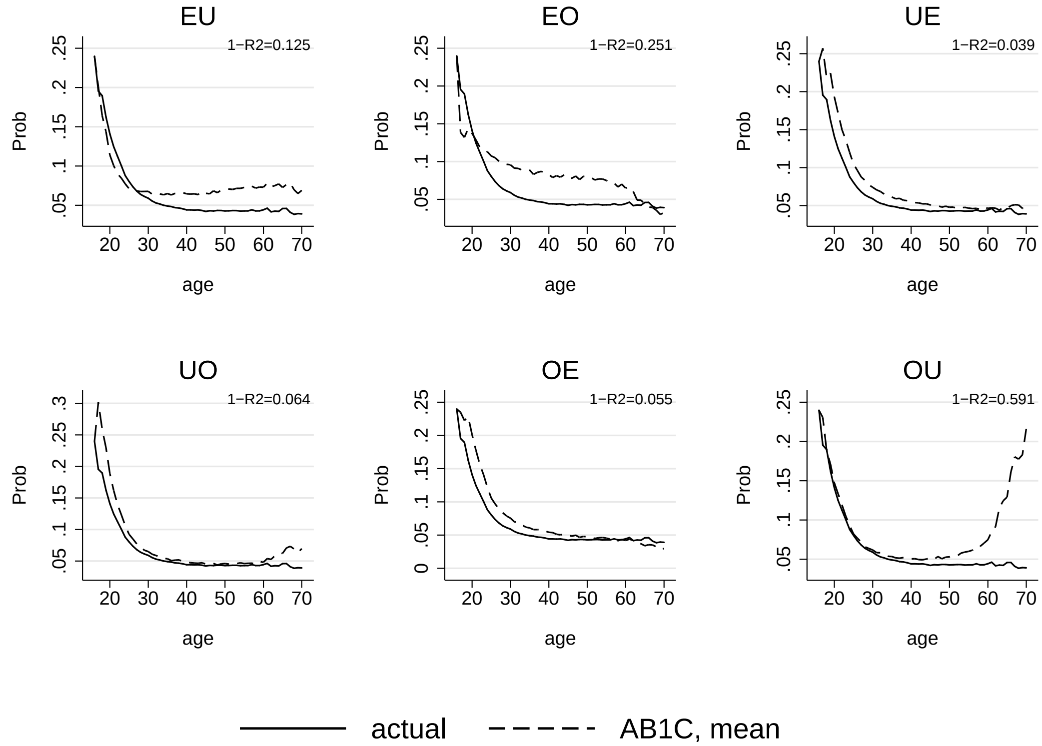
Figure A81: Markov-Chain Simulated Unemployment and Participation: Corrected for Time-Aggregation



Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

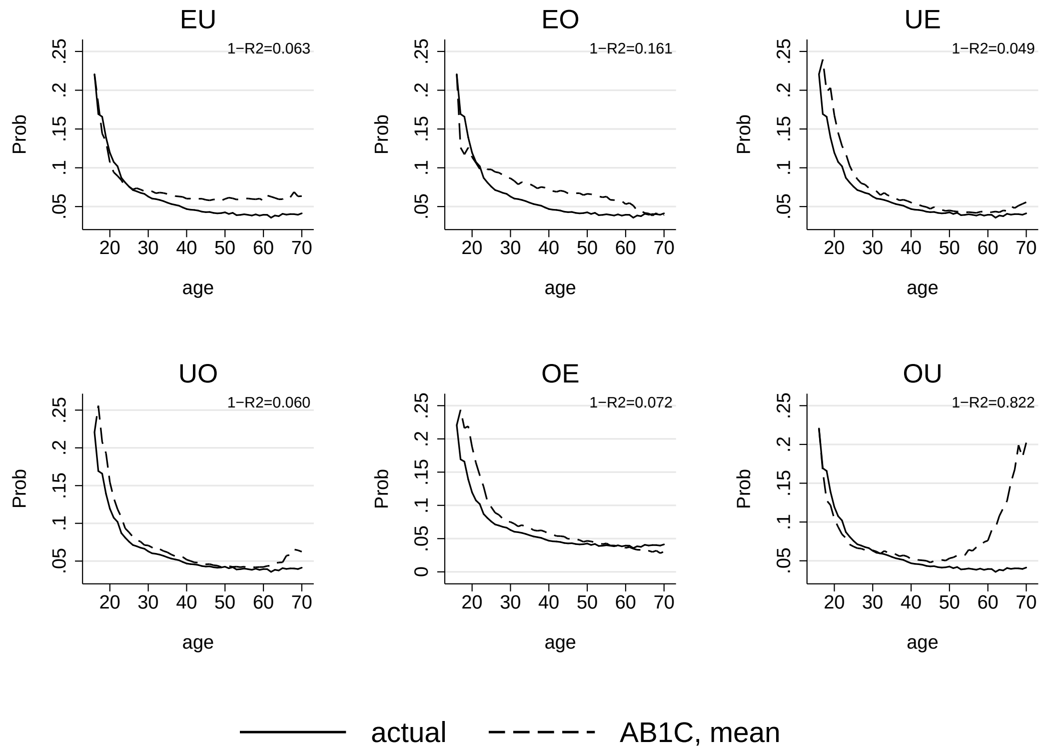
F.4 AB1C Decomposition with TA Corrected Probabilities in Various Frequencies

Figure A82: AB1C Decomposition of the Importance of Flows: Unemployment, Males, TA Monthly



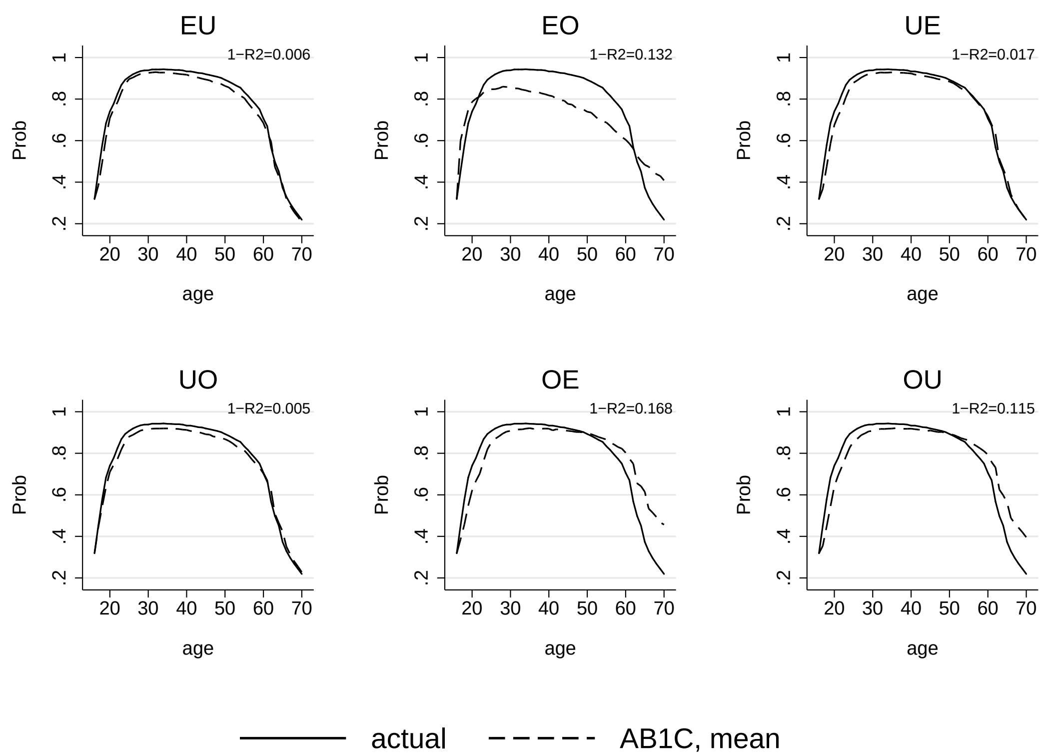
Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A83: AB1C Decomposition of the Importance of Flows: Unemployment, Females, TA Monthly



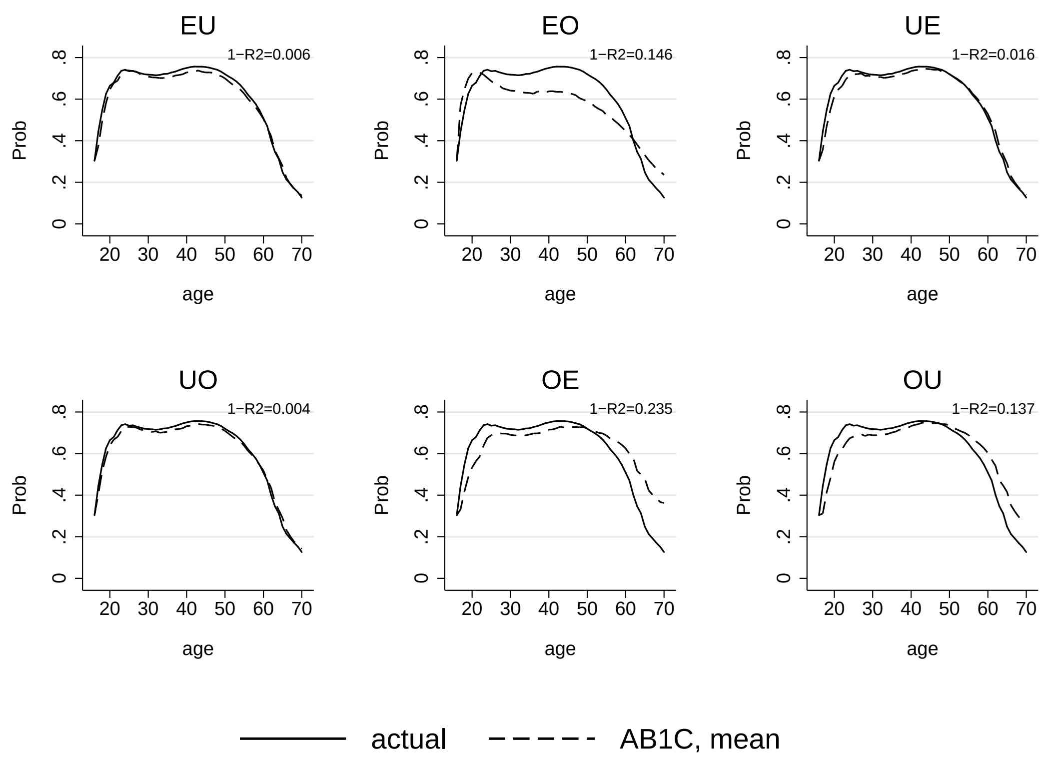
Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A84: AB1C Decomposition of the Importance of Flows: Participation, Males, TA Monthly



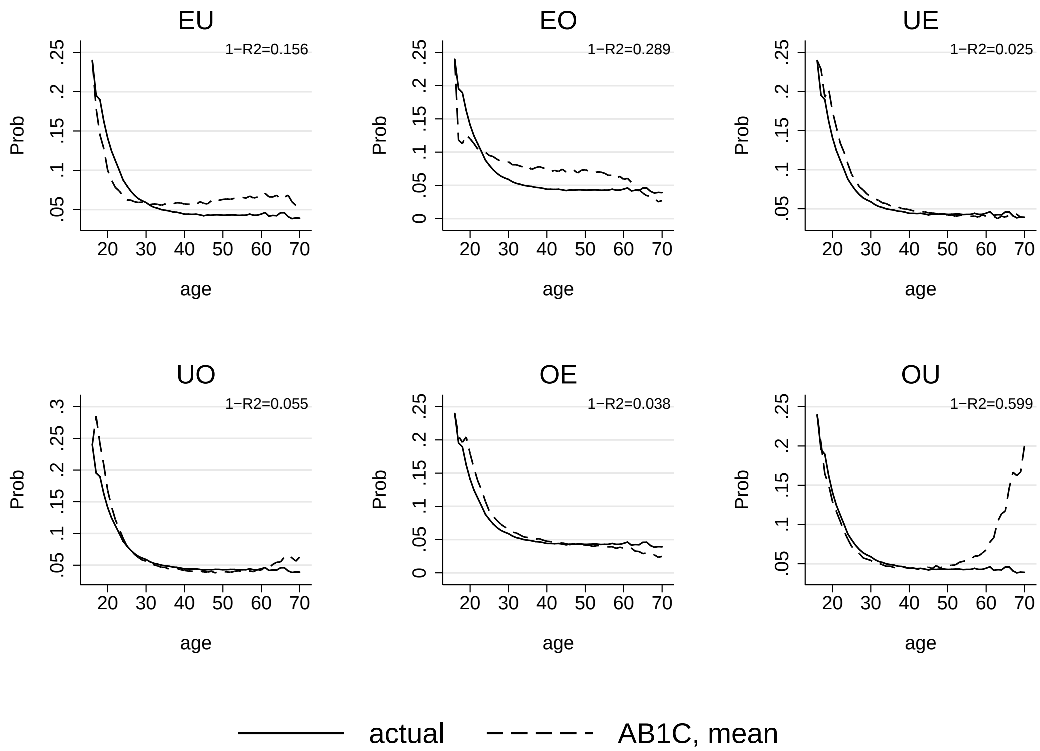
Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A85: AB1C Decomposition of the Importance of Flows: Participation, Females, TA Monthly



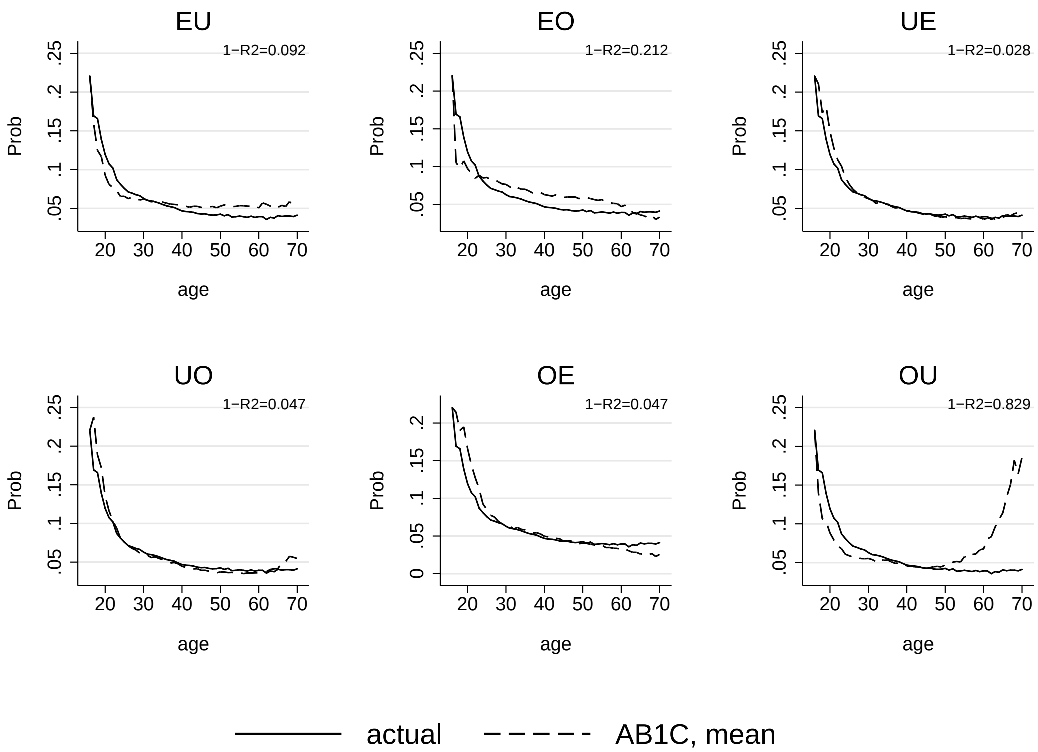
Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A86: AB1C Decomposition of the Importance of Flows: Unemployment, Males, TA Hourly



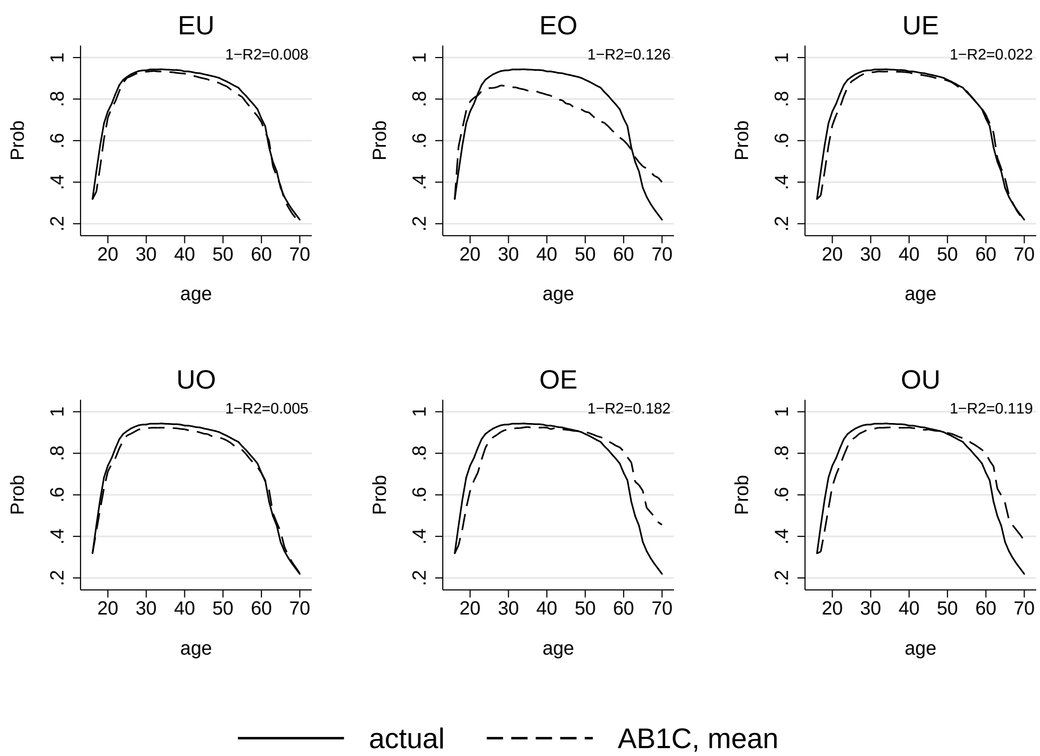
Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A87: AB1C Decomposition of the Importance of Flows: Unemployment, Females, TA Hourly



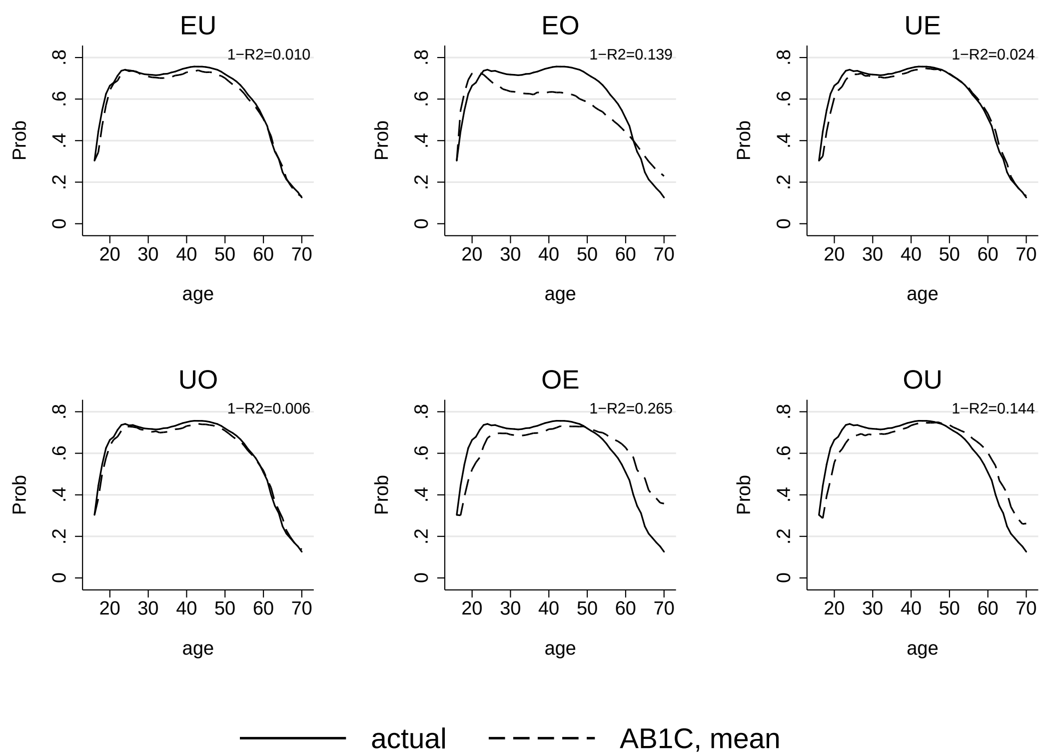
Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A88: AB1C Decomposition of the Importance of Flows: Participation, Males, TA Hourly



Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

Figure A89: AB1C Decomposition of the Importance of Flows: Participation, Females, TA Hourly



Note: Unconditional life-cycle profiles estimated via weighted OLS.Corrected for Time-Aggregation following Shimer (2013).

G Misclassification (MC) Results

G.1 Method

It is well known in the literature that the estimation of transition probabilities from flow data is sensitive to misclassification (MC) error in recorded labour market states. Given our main results (i.e., importance of the participation margin for explaining life-cycle unemployment and participation) any evidence of serious MC error might put in doubt our results, especially since Unemployment (U) and Out of the labour force (O) are states more likely to be coded with error.[3]

In this section we analyze the effects of MC error by using two alternative corrections proposed by the literature: The first approach, follows closely Feng and Hu (2013) (henceforth FH), who use a latent variable approach to estimate the probability of misclassification of the current true labour force state, given observed individual histories. The method in FH requires the use of individual longitudinal information on labour force states, which is available from the CPS since individuals are followed a total of 8 months (two sets of four consecutive months, separated by an eight month hiatus). We apply the FH method using labour force histories of three consecutive months, from where we extract the age-specific joint probability of transiting through specific paths: For example, given observed information for individuals aged i during months $t-1$, t and $t+1$, we can compute the set of joint probabilities

$$Pr(s_{t-1} = j, s_t = k, s_{t+1} = l)$$

with $\{j, k, l\} \in \{E, U, O\}$. In words, for each age group, we can calculate the fraction who, for example, transited from employment in period $t-1$, to employment in period t and eventually to unemployment in period $t+1$; i.e., history **EEU** has a related probability $Pr(E_{t-1}, E_t, U_{t+1})$ over all those individuals who have non-missing information for those three consecutive months. The FH method uses a combination of these probabilities to compute $Pr(s_t^*|s_t)$ with $s \in \{E, U, O\}$ (the probability of the true labour force state being s_t^* given reported state s_t) through an eigenvalue-eigenvector decomposition of a suitable arrangement of the above mentioned probabilities into matrices. Then, using results from Poterba and Summers (1986), one can compute worker flows and transition probabilities using the true state probabilities. We depart from the FH methodology in two ways: we use information from three consecutive months, while they use information on months $t-9$, t and $t+1$. We make this choice in order to minimize data requirements, since we need to be able to compute these probabilities for each age group: requiring a match between months $t-9$, t and $t+1$, might produce too much attrition due to the added difficulty of matching workers across the eight month hiatus in the CPS survey. Our second departure from the FH methodology is also related to the issue of sample size: we average the resulting age-specific probabilities arising from

[3]This has been pointed out by Abowd and Zellner (1985) and Poterba and Summers (1986).

the FH procedure across 3 ages, in order to minimize the effect of outliers due to low sample size (specially for younger and older workers). That is, age i corrected stocks and transition probabilities reflect the average of ages $i-1$ to $i+1$.

Second, we follow Elsby, Hobijn, and Şahin (2013) (henceforth EHS), who perform a mechanical recoding of unemployment-nonparticipation cyclers. By matching individuals along the entire longitudinal dimension of the CPS,[4] EHS recode ”obvious” cases of MC: for example, a worker who in four consecutive months is observed as **OOUO** (spends the first two months out of the labour force, the next month as unemployed and the last month out of the labour force) is then recoded as **OOOO**. A similar recoding takes place for histories **OUOO**, **UUOU**, **UOUU** and so on.[5]

Two main differences exist between this procedure and the one from FH: (i) FH require less data (three matched months instead of four) and (ii) the FH method provides ”corrected” transition probabilities between all states, not only for those between the unemployment (U) and the out of the labour (O) states.

Figures A90 and A91 present life-cycle profiles for each transition probability, as they appear in the main body of the paper (raw), corrected as in Feng and Hu (2013) (FH adj) and corrected as in Elsby, Hobijn, and Şahin (2013) (EHS adj). Notice that the EHS correction shows differences for the UO and OU profiles mostly, while the FH adjusts all probabilities downwards. More importantly for our results, the MC error seems to have a very mild life-cycle component: besides the last years for OE and OU, the difference between raw and corrected transition probabilities doesn't move systematically with age. This can also be seen from figures A94 to A96, where the probability of being recorded in labour state X given true state X^* are shown to be very stable over the life-cycle with one exception: The probability of not being coded as unemployed when truly unemployed is higher when the worker has less than 20 and more than 65 years of age (inverted u-shaped of $Pr(U|U^*)$) which is intuitive, if we think of these stages as the ones where workers are more ambivalent between participating or not, for example, due to schooling choice decisions for the young and retirement decisions for the older workers. On the other hand, $Pr(O|U^*)$ is higher at the beginning and end of the life-cycle, which is the flip side of the previous pattern.

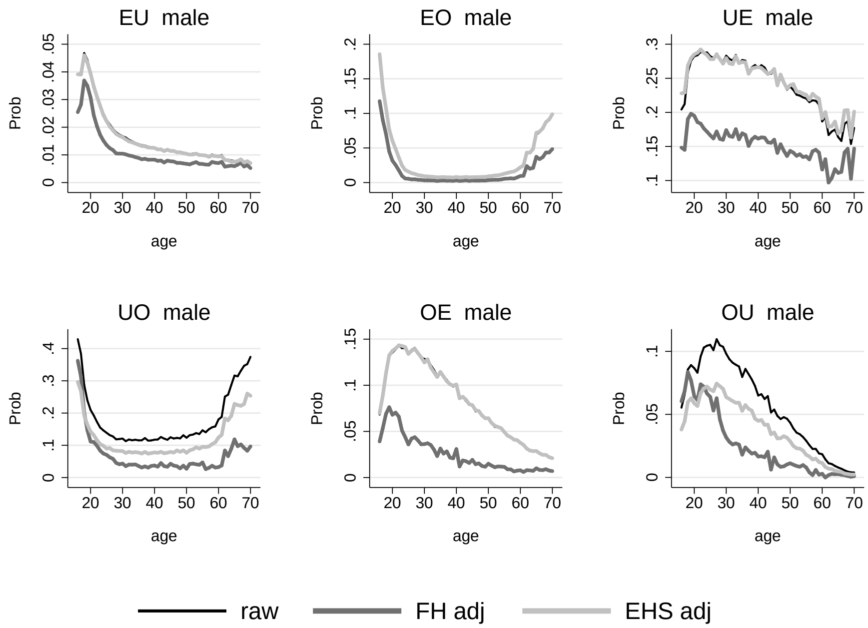
However, when we compute unemployment and participation profiles using the corrected data, our results differ marginally from those obtained using the raw transition probabilities. The same applies for our AB1C decomposition exercises for both unemployment and participation, for both genders. Our interpretation of these results is similar to the one found usually in the literature: at the aggregate level, these MC errors tend to cancel each other, producing insignificant effects on flows and rates.

[4]The method requires four consecutive months of information per worker, as opposed to only two months needed for the standard flow estimations in the body of the paper.

[5]See table 2 of Elsby, Hobijn, and Şahin (2013) for a complete list of cycles being recoded.

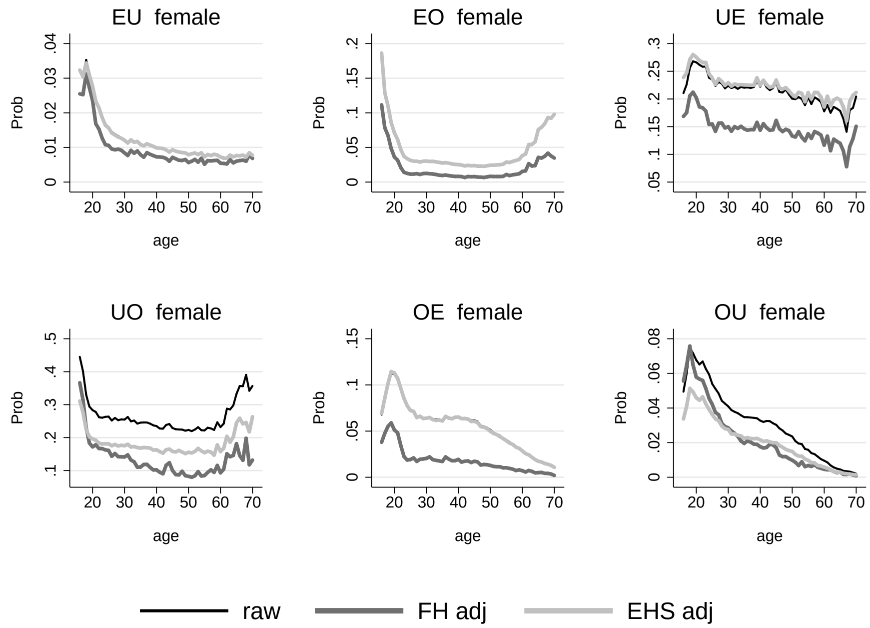
G.2 Monthly Corrected Flows and Stocks

Figure A90: Life-Cycle Profiles of Worker Flows Transitions: Males, Corrected for Misclassification.



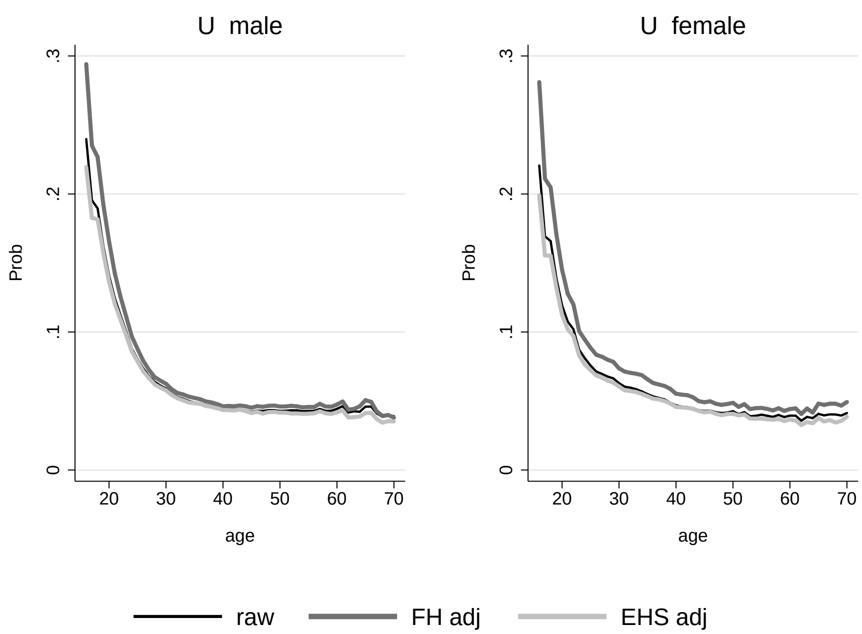
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification.

Figure A91: Life-Cycle Profiles of Worker Flows Transitions: Females, Corrected for Misclassification.



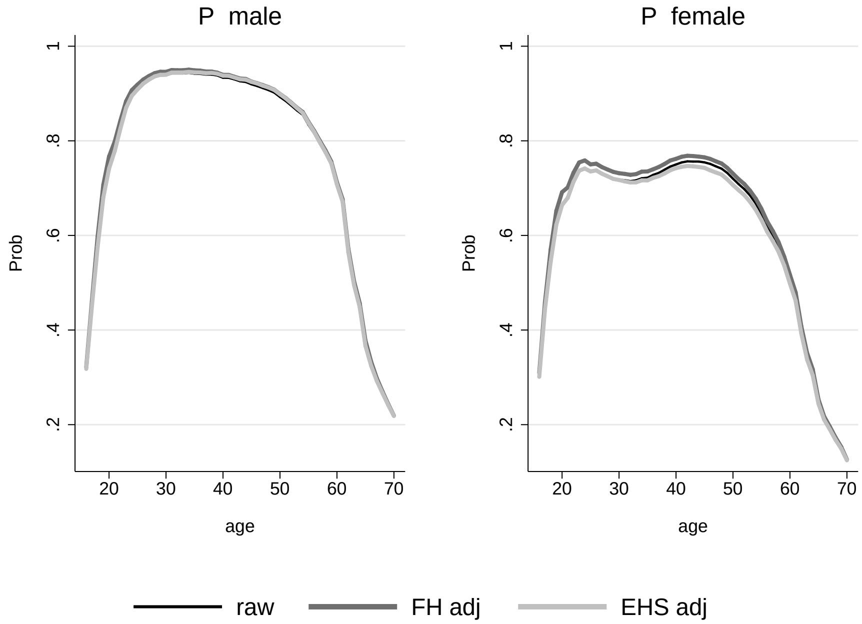
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification.

Figure A92: Life-cycle Unemployment Rate Profiles, Corrected for Misclassification.



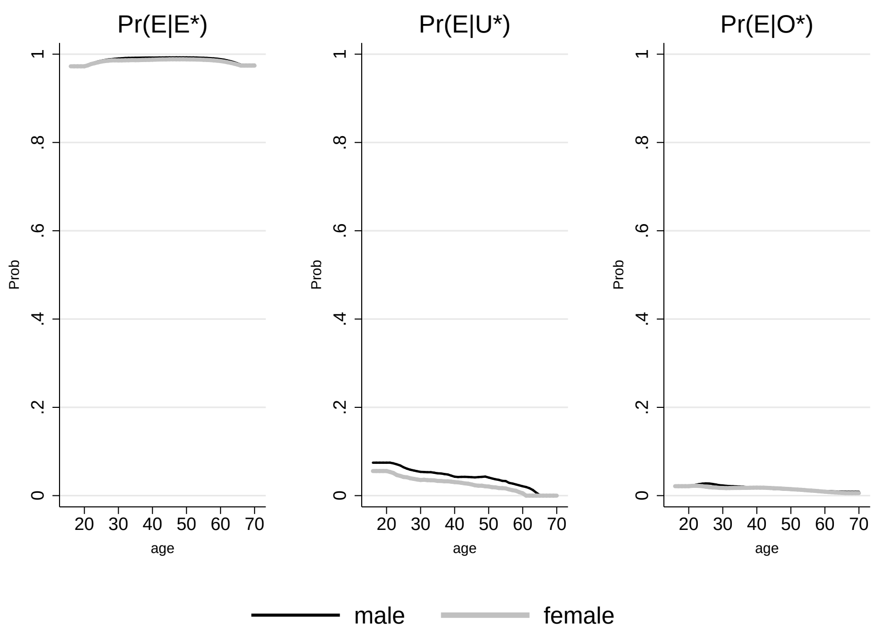
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification.

Figure A93: Life-cycle Participation Rate Profiles, Corrected for Misclassification.



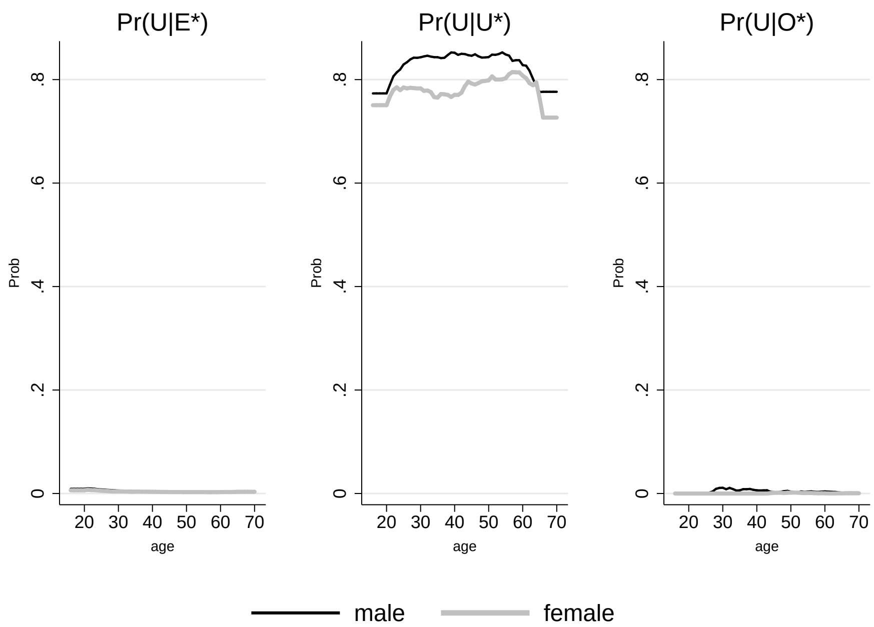
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification.

Figure A94: Life-Cycle Estimated Misclassification Errors for Employment



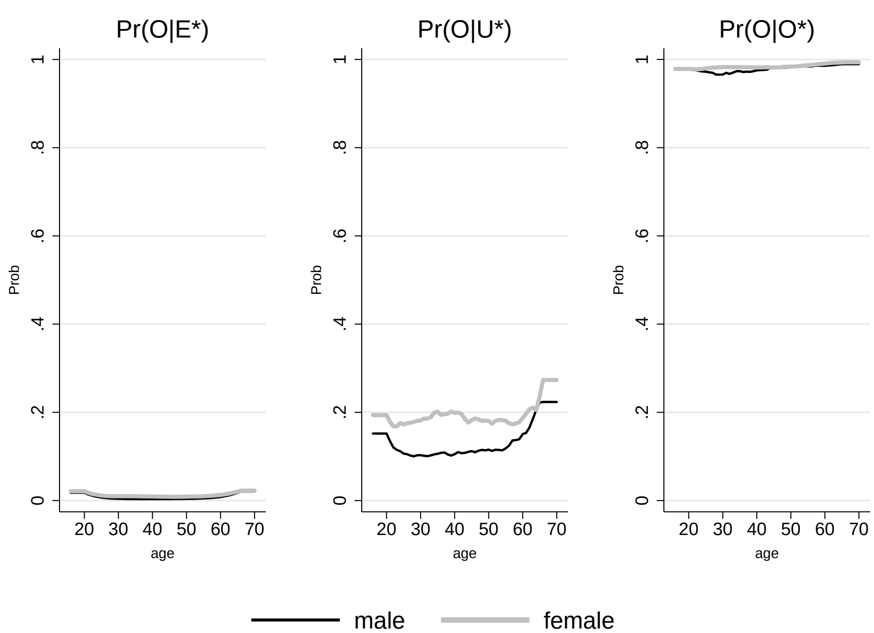
Note: Computed on monthly unconditional estimates following Feng and Hu (2013).

Figure A95: Life-Cycle Estimated Misclassification Errors for Unemployment



Note: Computed on monthly unconditional estimates following Feng and Hu (2013).

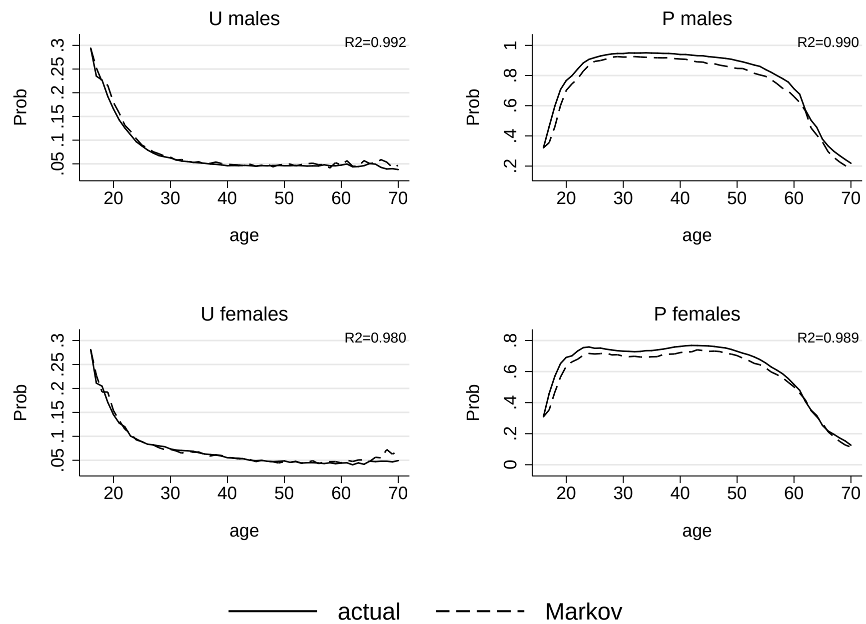
Figure A96: Life-Cycle Estimated Misclassification Errors for Inactivity



Note: Computed on monthly unconditional estimates following Feng and Hu (2013).

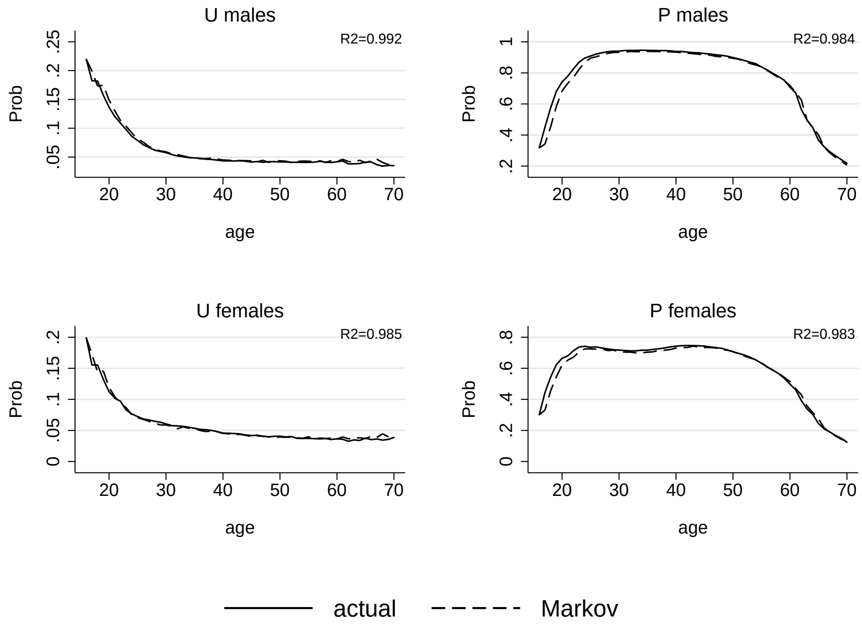
G.3 Markovian Simulations with MC Corrected Probabilities

Figure A97: Life-Cycle Unemployment and Participation Profiles, Corrected for Misclassification following Feng and Hu (2013).



Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Feng and Hu (2013).

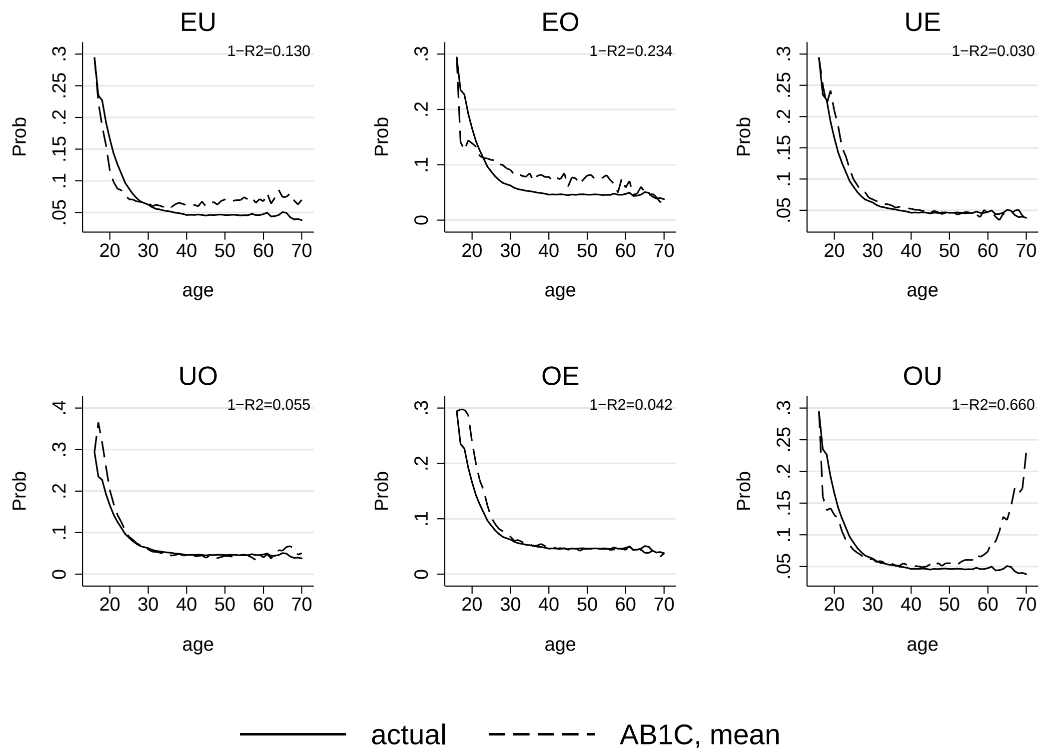
Figure A98: Life-Cycle Unemployment and Participation Profiles, Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).



Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).

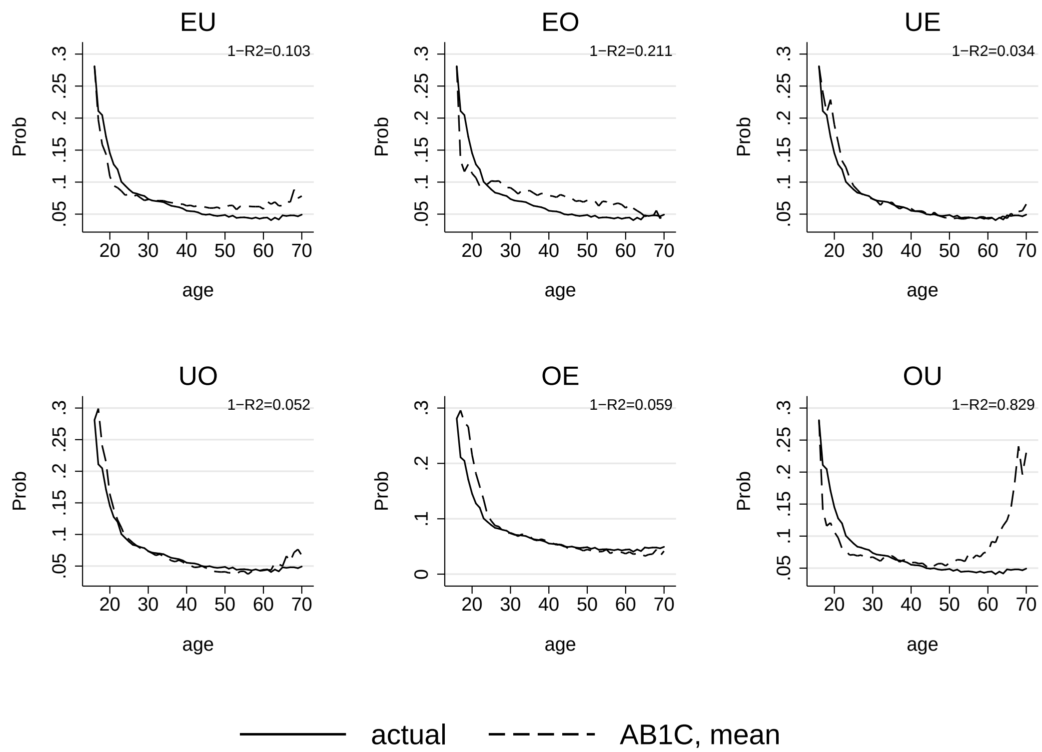
G.4 AB1C Method with MC Corrected Probabilities

Figure A99: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Corrected for Misclassification following Feng and Hu (2013).



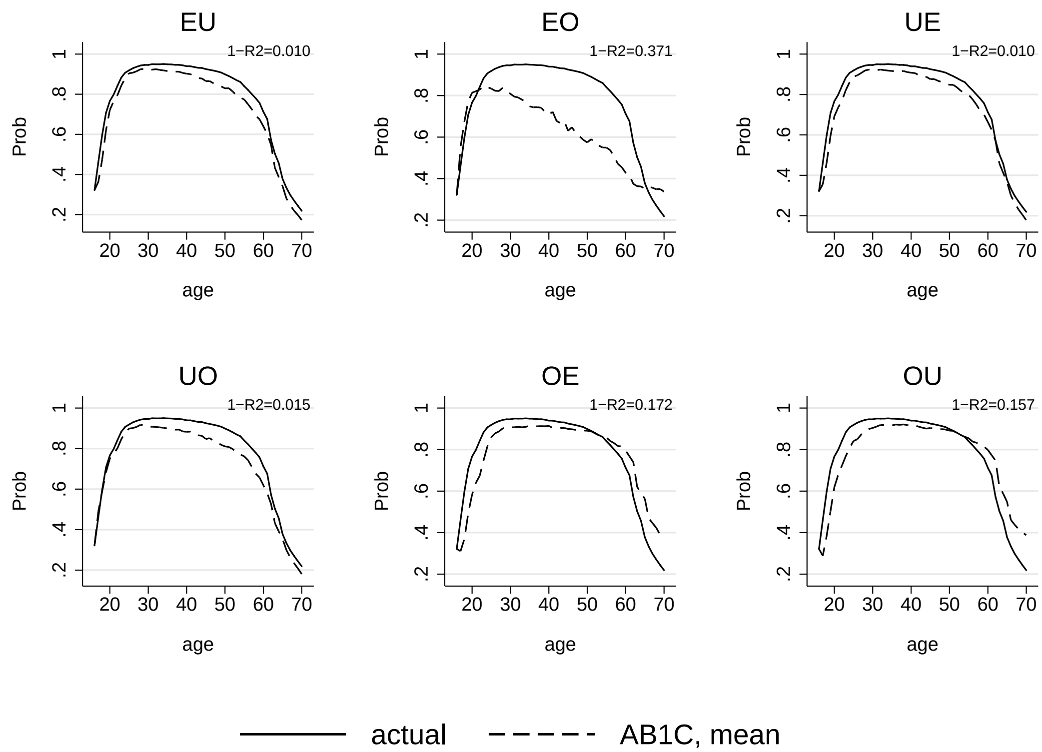
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Feng and Hu (2013).

Figure A100: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Corrected for Misclassification following Feng and Hu (2013).



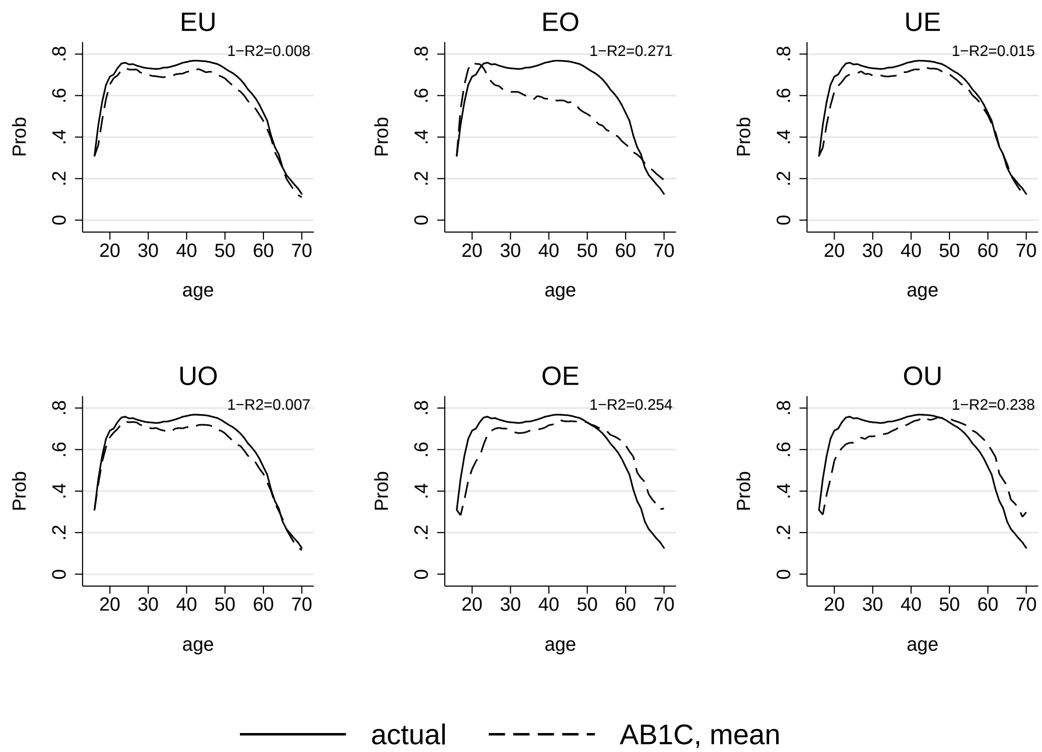
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Feng and Hu (2013).

Figure A101: AB1C Decomposition of the Importance of Flows: Participation, Males, Corrected for Misclassification following Feng and Hu (2013).



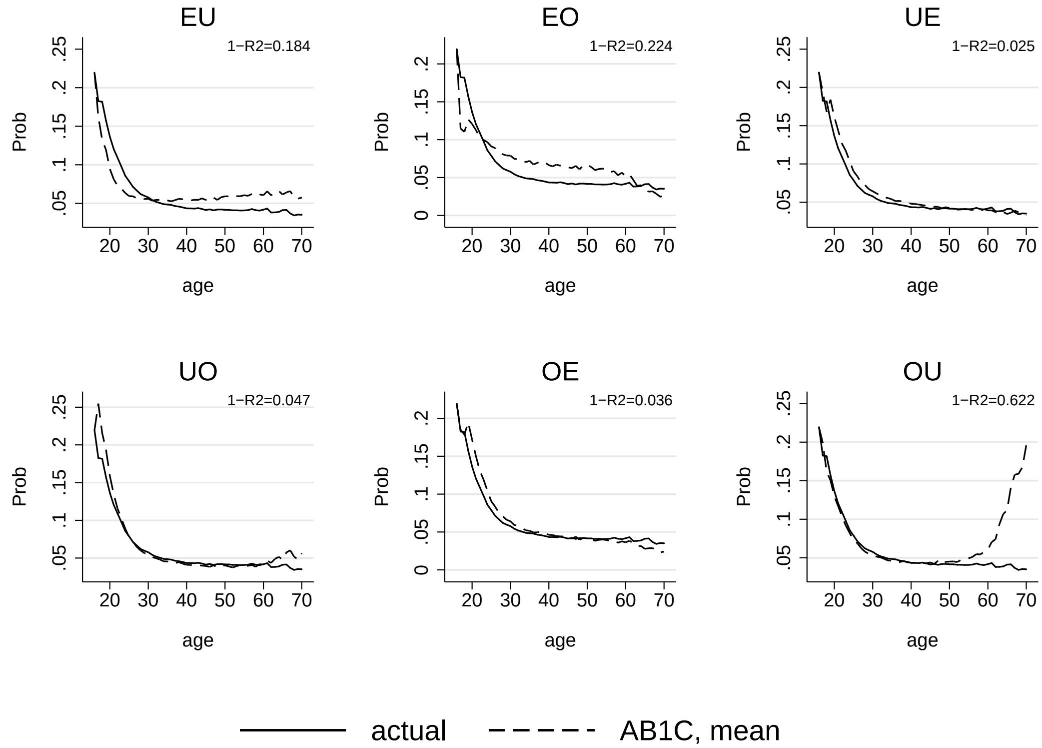
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Feng and Hu (2013).

Figure A102: AB1C Decomposition of the Importance of Flows: Participation, Females, Corrected for Misclassification following Feng and Hu (2013).



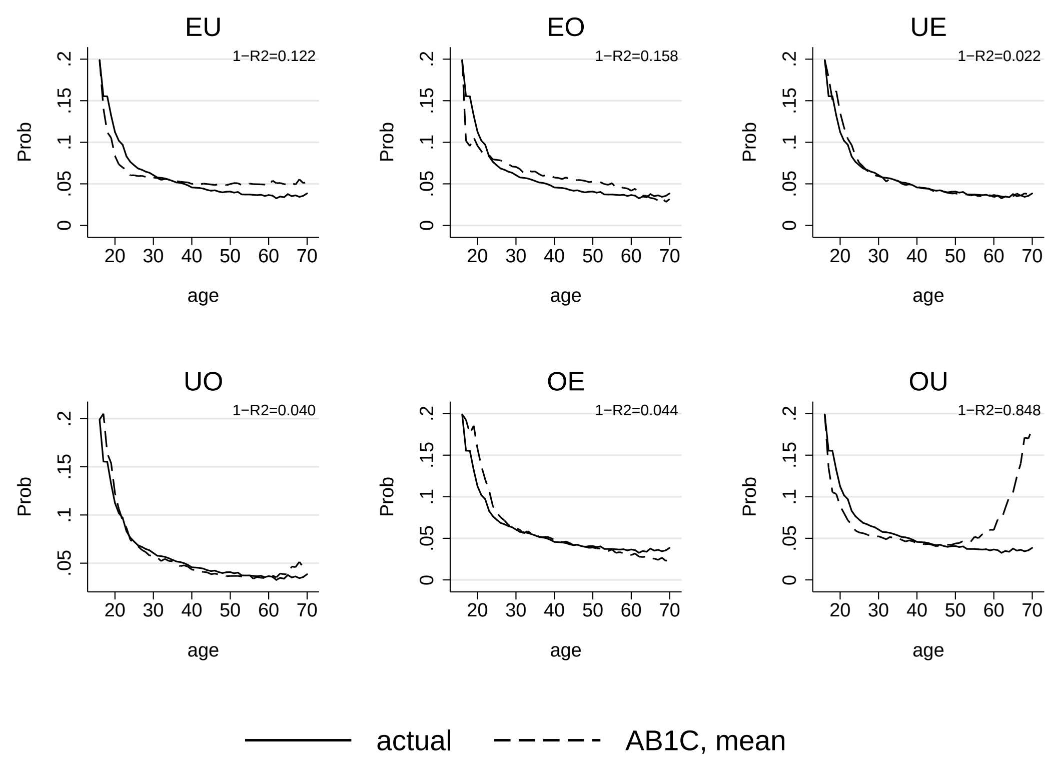
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Feng and Hu (2013).

Figure A103: AB1C Decomposition of the Importance of Flows: Unemployment, Males, Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).



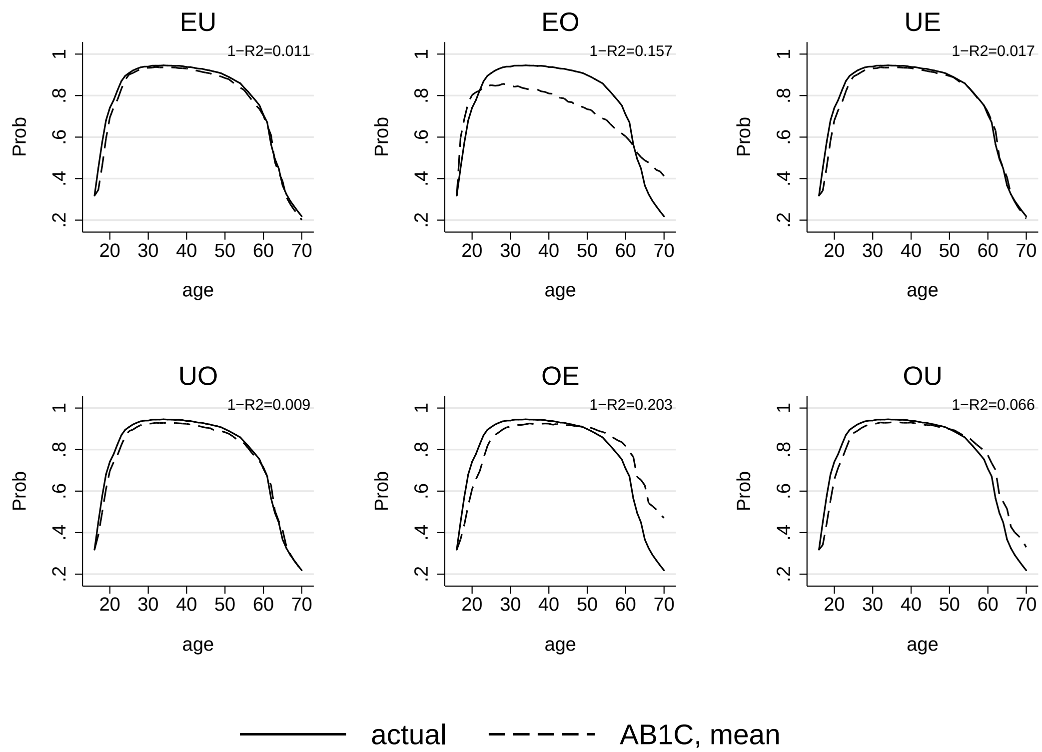
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).

Figure A104: AB1C Decomposition of the Importance of Flows: Unemployment, Females, Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).



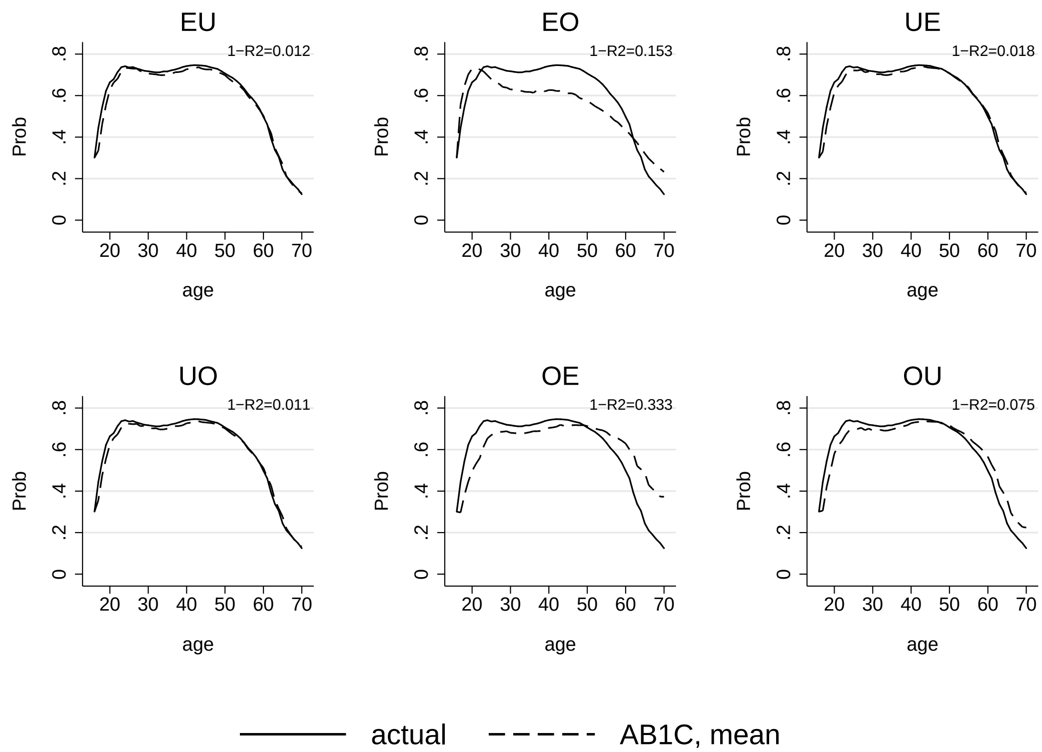
Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).

Figure A105: AB1C Decomposition of the Importance of Flows: Participation, Males, Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).



Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).

Figure A106: AB1C Decomposition of the Importance of Flows: Participation, Females, Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).



Note: Unconditional life-cycle profiles estimated via weighted OLS., Corrected for Misclassification following Elsby, Hobijn, and Şahin (2013).