UNIVERSITY OF Southampton
School of Social Sciences

Economics Division
University of Southampton
Southampton SO17 1BJ, UK

Discussion Papers in
Economics and Econometrics

Title: The Marriage Unemployment Gap

Authors : Sekyu Choi (University of Bristol) & Arnau Valladares-Esteban (University of Southampton)

No. 1509

This paper is available on our website
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ISSN 0966-4246

The Marriage Unemployment Gap

Sekyu Choi
University of Bristol

Arnau Valladares-Esteban
University of Southampton*

December 1, 2015

Abstract

In this paper we document that married individuals face a lower unemployment rate than their single counterparts. We refer to this phenomenon as the marriage unemployment gap. Despite the dramatic demographic changes in the labor market over the last decades, this gap has been remarkably stable both for men and women. Using a flow-decomposition exercise, we assess which transition probabilities (across labor force states) are behind the marriage unemployment gap. We find that, for men, the higher attachment to employment of married males is the main driver of the gap. For females, we find that the participation margin plays a crucial role.

Keywords: Households, Marriage, Unemployment, Worker flows.

JEL Codes: **E24, J12, J64**

*E-mail: sekyu.choi@bristol.ac.uk and arnau.valladares@gmail.com. We thank Nezih Guner, Stefania Albanesi, Yuliya Kulikova, Joan Llull, Brendon McConnell, and seminar participants at UAB, CEA-Universidad de Chile, ENTER Jamboree 2013, 2014 SAEe, University of Southampton, and the 2013 SED meetings in Seoul, South Korea for thoughtful comments and discussion. Sekyu Choi gratefully acknowledges financial support from the Spanish Ministry of Economy and Competitiveness through grant ECO2012-32392 and through the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2011-0075). All errors are ours.

1 Introduction

Over the last decades, the U.S. economy has experienced two major demographic and labor market changes. One of these changes is the secular decline in the proportion of married individuals in the labor force. The other is the dramatic increase in the employment rate of women, specially married women[1]. In this paper, we document that, despite these changes, there exists a stable and sizeable difference between the unemployment rate of married and single men[2]. In particular, married men face a lower unemployment rate than single men. For women, we document the emergence of a similar gap in the 1980s and its stabilisation since then. The emergence of the gap for women, coincides with the rise in the employment rate of married females and its convergence with the employment rate of single females. We name the phenomenon of lower unemployment rate for married individuals the marriage unemployment gap.

We analyse monthly data from the Current Population Survey (CPS) and compute labor market stocks and worker flows between employment, unemployment, and non-participation by marital status and gender. We adjust the data for time aggregation, misclassification biases, and the different observable characteristics of married and single individuals. Using a similar decomposition method as in Shimer (2012), we assess which of the transitions are more relevant in accounting for the unemployment rate differences between married and single individuals. We find that for males, the higher employment exit probabilities exhibited by single males are the main determinant of the gap. For females, we find that the participation margin also plays a fundamental role. Importantly, we find that the contribution of these channels to the gap is stable over time.

This paper is related to different streams of the literature. Firstly, as in Shimer (2012), Elsby, Hobijn, and Sahin (2015), or Choi, Janiak, and Villena-Roldán (2014) we assess the importance of worker flows on labor market stocks. Secondly, this paper relates to the literature studying another striking difference between labour market outcomes of married and single individuals, namely the marriage wage premium (Antonovics and Town (2004) is one example of this literature). Finally, our analysis aims to provide a rich set of stylised facts to the growing theoretical literature on joint employment search, see Albrecht, Anderson, and Vroman (2010), Ek and Holmlund (2010),

[1] See Greenwood, Seshadri, and Yorukoglu (2005); Greenwood and Guner (2008), Attanasio, Low, and Sánchez Marcos (2008), or Stevenson and Wolfers (2007) among many others.

[2] Throughout this paper, we define the married group as those workers who, in our dataset, claim to be married and their spouse is present in the household at the time of the survey. In the single group, we pool never married, separated, divorced, and widowed individuals.

or Guler, Guvenen, and Violante (2012), among others.

2 Data

We use the monthly files from the Current Population Survey (CPS) as our main data source. Since survey respondents are followed for up to four consecutive months, we use a standard age/sex/race linking procedure to obtain longitudinal information on workers across months.[3] We consider all workers aged 16 and above (our results are robust to different age restrictions) between January of 1976 and December of 2013. From the data, we compute the proportion of workers during each month in three labor market states: employment (E), unemployment (U) and inactivity/out of the labor force (O). We also compute monthly transition probabilities as the number of workers who transit from one state $\{E, U, O\}$ in month t to a subsequent state $\{E, U, O\}$ in month $t+1$, divided by the total number of workers in the original state. Below, we discuss three adjustments we perform on the data.

Controlling for observables. When comparing married and single individuals, some of the differences in outcomes may be attributed to differences in the demographic composition of each group. In order to control for these, we adjust our sample using a matching algorithm:[4] we create bins for observable characteristics (gender, race, age, census division, education, and the number of children in the household), then, we eliminate bins that contain individuals from only one marital status. We iterate over the coarseness of variable definitions (e.g., precison of education levels or race categories) in the previous step, such that we do not eliminate more than 5% of the sample in this elimination step. Finally, in each bin we perform a bootstrap-like replication of observations at random, in order to equate the number of married and single individuals. In our final sample, the demographic characteristics of the single and married group are exactly identical.

The benefit of this procedure is two-fold. First, it is entirely non-parametric, so it does not impose any structure on the effect of observables on the variables of interest. Second, it allows us to compute the level of all labour market outcomes we are interested in controlling for the effect of observables. Note that any regression would only deliver the difference between married and singles individuals for each variable of interest. In section B of the appendix, we show a comparison between our method and a Probit regression.

[3] See Shimer (2012) for a description of the methodology.

[4] See Angrist (1998).

Time aggregation and classification errors. The use of the data in its raw format (stocks and transition probabilities) suffers from two well known issues: time aggregation bias and classification errors. Time aggregation bias arises since we only observe individual information at fixed time intervals (one month apart in the case of the CPS), and have no information of what occurs in the meantime. For example, if we observe an individual who is unemployed in period t and then as employed in period $t+1$, we record an unemployment to employment (UE) transition. However, intermediate transitions could have occurred during the weeks inside the month. For example, a UE followed by EU and a final UE transition could be encompassed by the originally observed, month-to-month UE transition. The two latter transitions are missed by the flow construction method.[5] In this paper we follow Shimer (2012) and Elsby, Hobijn, and Sahin (2015) and correct for this bias using an eigenvalue-eigenvector decomposition technique.

Classification errors, on the other hand, are related to erroneous codification and/or reporting of labor market states in surveys as the CPS. Since the distinction of whether one is looking for a job or not might be fuzzy at the individual level, erroneous classification of individuals as unemployed instead of inactive (and viceversa) might be significant. As noted by Abowd and Zellner (1985) and Poterba and Summers (1986), transition probability estimates between U and O can be especially affected by misclassification. In this paper, we are comparing unemployment rates and labor market transitions for different sub-groups of the population, who have significantly different levels of attachment to the labor force. Taking care of this classification error is thus crucial to get a correct view of heterogeneity in unemployment rates and its sources. In what follows, we apply a procedure suggested in Elsby, Hobijn, and Sahin (2015) which entails "ironing" out cycles between unemployment and inactivity. For this method, we make full use of the longitudinal aspect of the CPS and merge four consecutive months of data for each worker (when possible). We then recode "U" to "O" whenever the "U" state is deemed to be temporary and likely to be misclassified (and vice versa). For example, an observed four-month individual employment history of the form $OUOO$ (a month out of the labor force, followed by a month unemployed, followed by two months out of the labor force) is changed to $OOOO$. In the same way, we replace an observed $UOUU$ history with $UUUU$.[6]

[5] This was first noted by Darby, Haltiwanger, and Plant (1986).

[6] See Elsby, Hobijn, and Sahin (2015) for a complete list of employment histories subject to recoding.

3 Stocks and Flows

Figures 1 and 2 show the employment to population $E/(E+U+O)$, and the unemployment rate $U/(E+U)$, respectively. Both figures are based on our adjusted sample, and are divided by gender and marital status.

(a) Males (b) Females

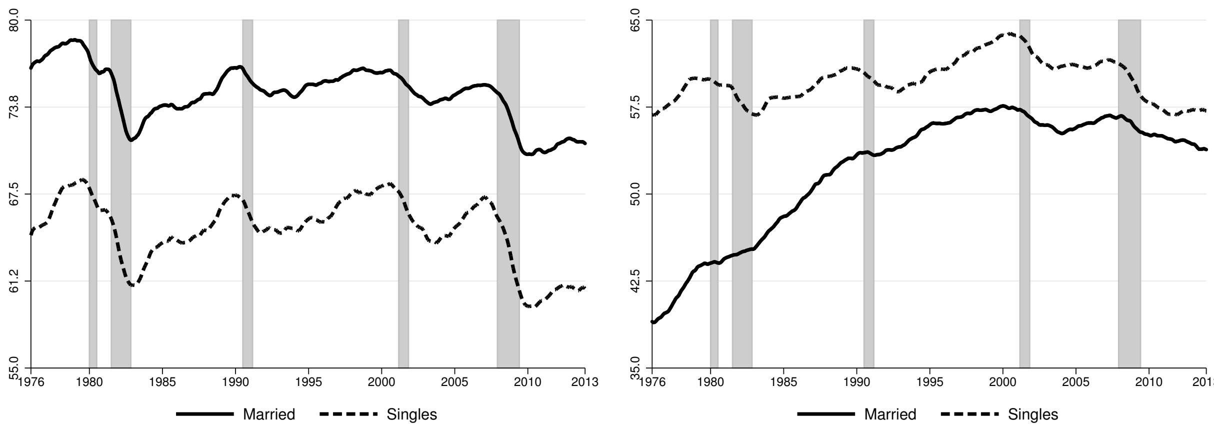

Figure 1: Employment rate by marital status. CPS 1976:1-2013:12. Corrected for classification error. Artificial sample to control for observables (see main text). Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

(a) Males (b) Females

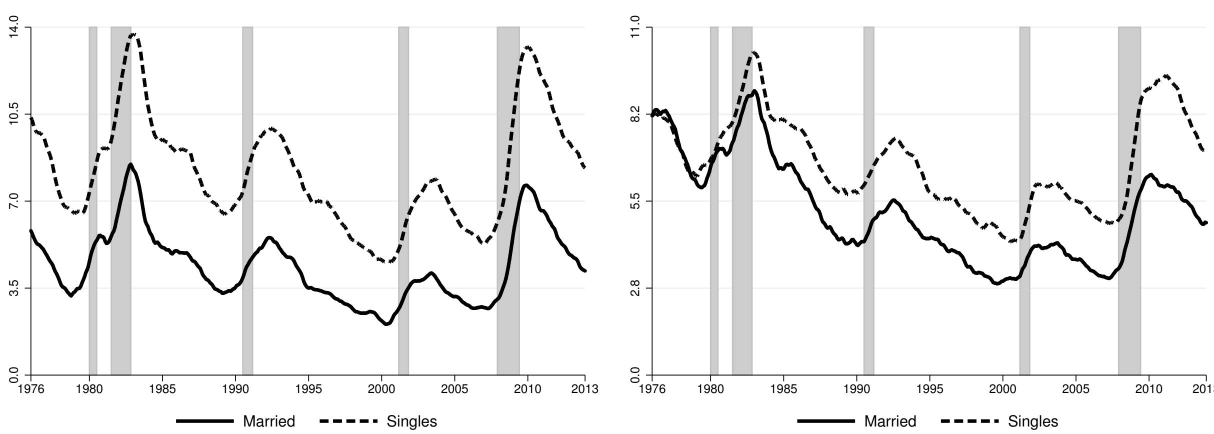

Figure 2: Unemployment rate by marital status. CPS 1976:1-2013:12. Corrected for classification error. Artificial sample to control for observables (see main text). Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

The figures show that the employment rates have been stable in our sample, except for married females: they experience a sharp increase in employment rates from the start of our sample (1976) to around the year 2000, time at which employment rates flatten for them. Note also that employment rates are higher for married men compared to single males, while the opposite is true for females. Finally, employment loses are stronger for males (of both marital states) during recessions, shown in the figures as gray vertical bars, which represent National Bureau of Economic Research (NBER) recession dates.

As for unemployment rates, both genders exhibit higher rates when one considers the single sample as opposed to the married one. This is what we name the marriage unemployment gap. The exception for this, is the case of females during the second half of the 70s, period when unemployment rates by marital status are shown to be very close.

The stocks of employed, unemployed and inactive (thus employment and unemployment rates) are closely linked to the flows that each worker experience. Below we show transition probabilities for males and females, using our adjusted sample.

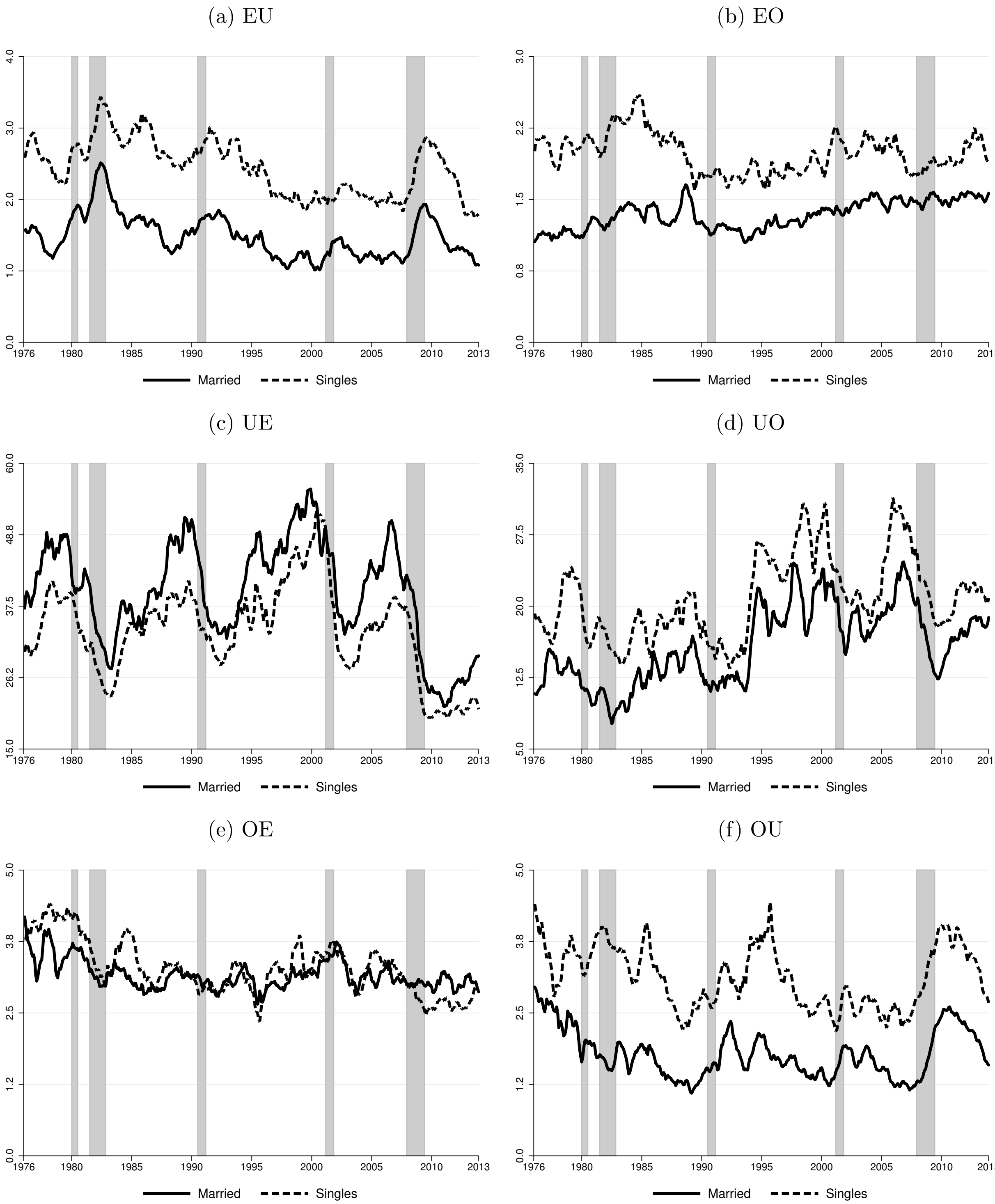

Figure 3: Labor market transitions for males. CPS 1976:1-2013:12. Corrected for time aggregation bias and classification error. Artificial sample to control for observables (see main text). Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

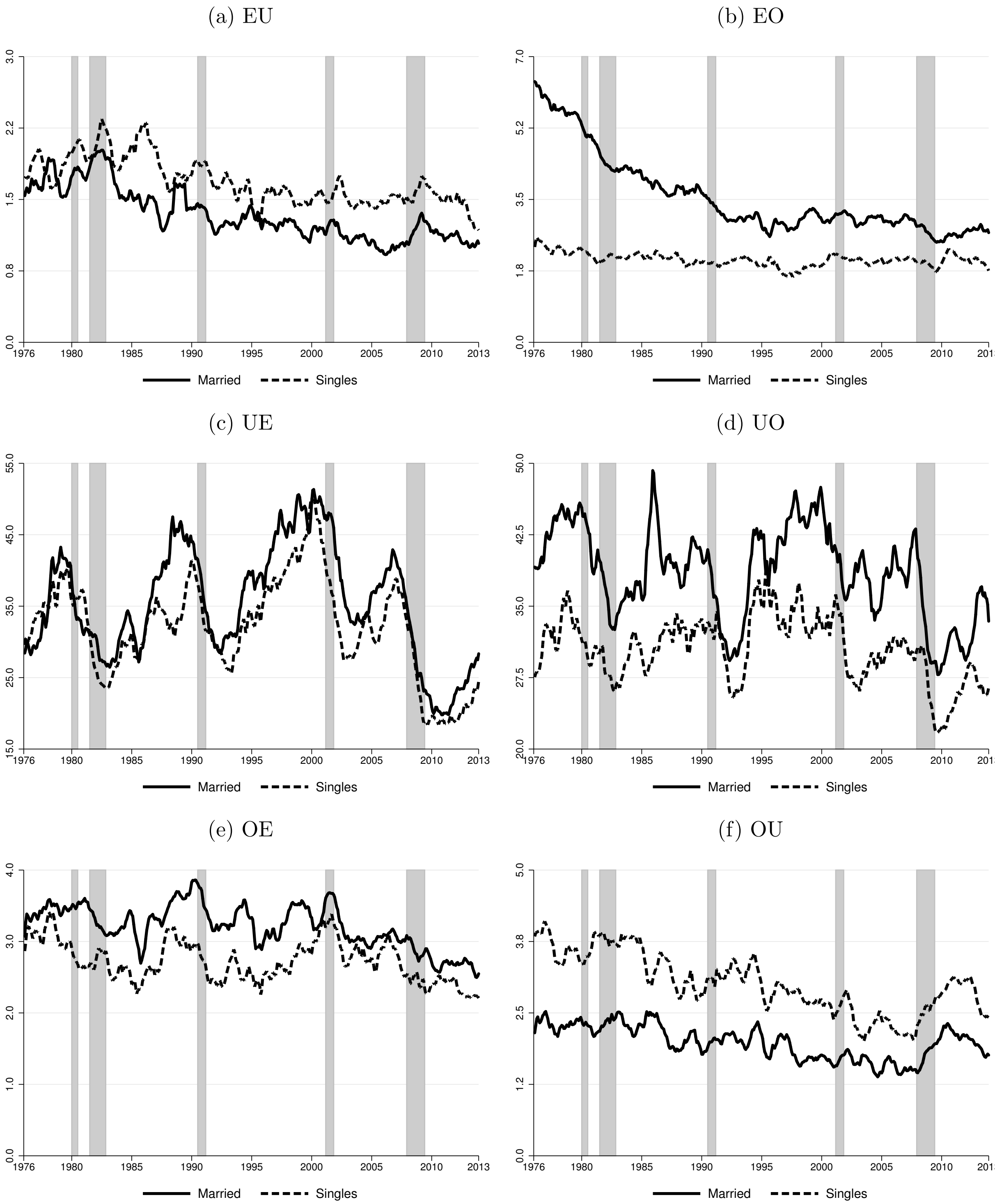

Figure 4: Labor market transitions for females. CPS 1976:1-2013:12. Corrected for time aggregation bias and classification error. Artificial sample to control for observables (see main text). Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

Figure 3, shows transition probabilities between E, U and O for male workers, separated by marital status, while figure 4 does the same for females. Notation XY denotes the probability of going from labor market state $X \in \{E, U, O\}$ to state $Y \in \{E, U, O\}$.

The figure for males shows that married male workers have a higher attachment to the labor market, since job separations, both to unemployment and inactivity, are lower for them than for singles. On the other hand, the married group has higher job finding rates out of unemployment, while they tend to exit to inactivity from unemployment at lower rates than single workers. In contrast, as seen in figure 4, transition probabilities for females are consistent with the idea that married women have lower attachment to the labor force: more specifically, transitions EO and UO are higher for married females than for single females, which points to the fact that married women are more likely to exit the labor force than singles, both from employment and unemployment.

4 A Decomposition Exercise

To account for differences in unemployment rates by agents of different marital status, we perform a similar decomposition exercise to Shimer (2012). We construct counterfactual unemployment rates for singles using all the transition probabilities for this group, except for one which we replace by the one corresponding to the married group. Hence, if the particular transition probability is important to explain the marriage unemployment gap, the counterfactual unemployment rate would be closer to the married rather than to the single unemployment rate.

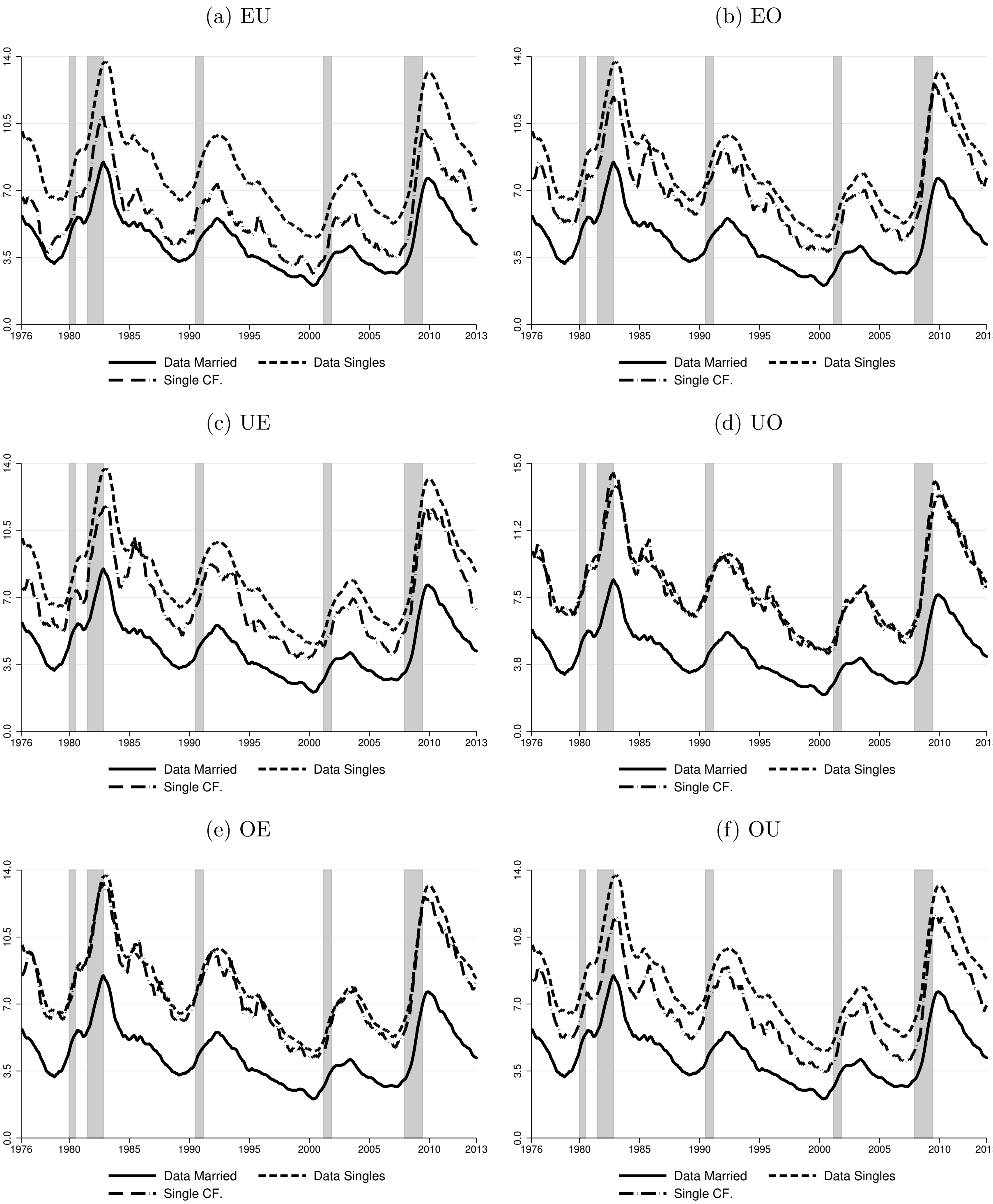

Figure 5: Counterfactual unemployment rates for single males, aged 16+, from 1976:1 to 2013:12

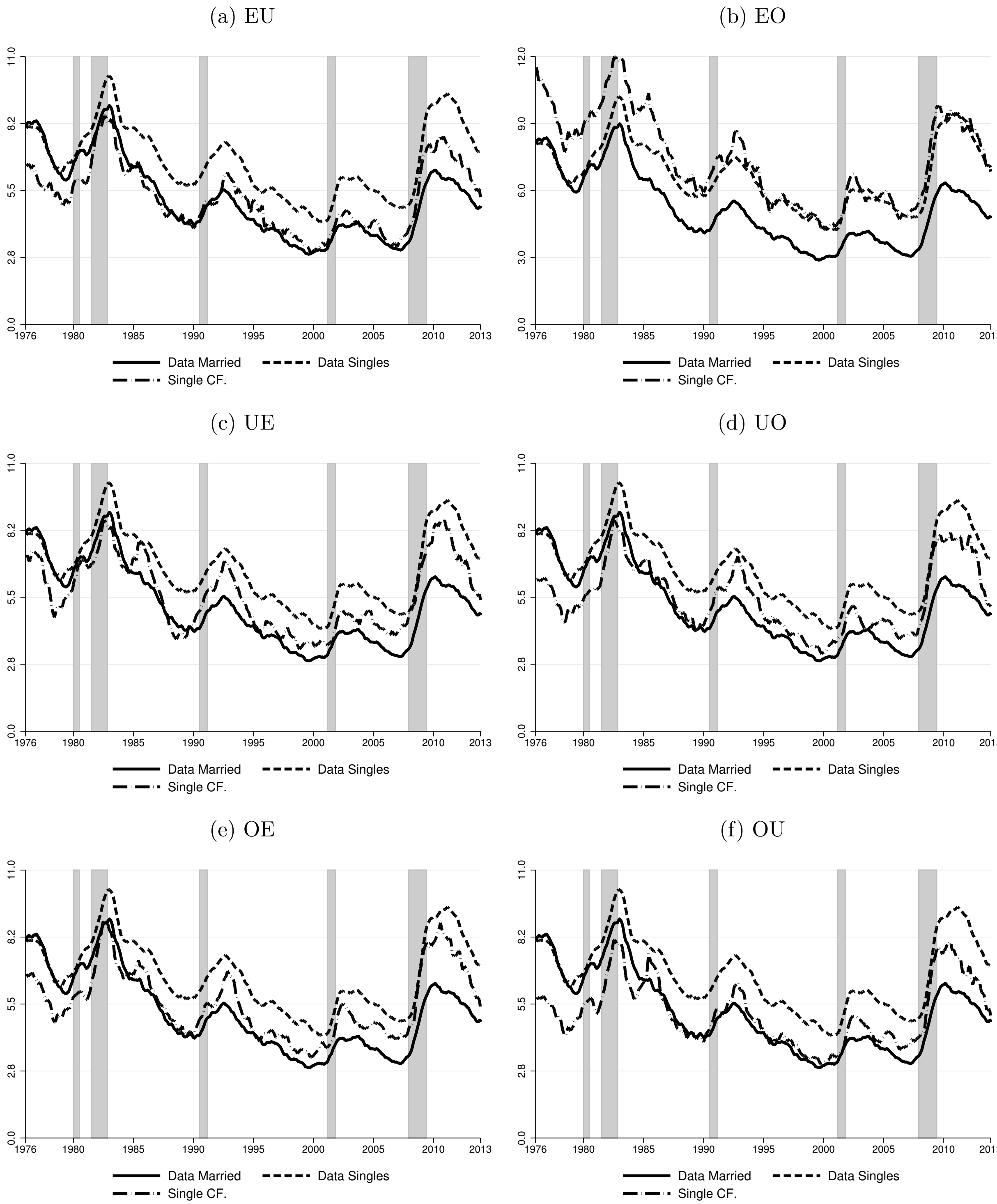

Figure 6: Counterfactual unemployment rates for single females, aged 16+, from 1976:1 to 2013:12.

In figure 5 we present the exercise for male workers while in table 1 we compute the average difference between the counterfactual (CF) single unemployment rate and the observed rate for the married population. For example, the first row of table 1 shows that when the single worker population experiences the EU transition probability of its married counterpart, the resulting unemployment gap between counterfactual singles and married workers is 1.36 percentage points; in contrast, transition UO accounts very little in explaining the gap, since the gap is maximum in the table (3.83 pp) and the single counterfactual line is almost identical to the observed single line in figure 5d. Thus, single workers experience a comparatively high unemployment rate because of the relatively high job losing rate (EU) they face compared to married workers. One interpretation of these results is that (part of the) difference between married and singles males comes from different match qualities in the jobs they find, which reflects on the observed durability of jobs and finally, in differential unemployment rates.

Transition	CF - Married
EU	1.36
EO	2.70
UE	2.53
UO	3.83
OE	3.38
OU	2.40

Table 1: Average difference (in %) between the counterfactual (CF) single unemployment rate (theoretical rate, when the associated transition probability is replaced by that of the married group) and the observed unemployment rate for married workers. Males.

Transition	CF - Married
EU	0.05
EO	2.31
UE	0.46
UO	0.33
OE	0.41
OU	0.00

Table 2: Average difference (in %) between the counterfactual (CF) single unemployment rate (theoretical rate, when the associated transition probability is replaced by that of the married group) and the observed unemployment rate for married workers. Females.

For female workers, transitions between employment and unemployment (EU and UE) are relevant to explain the marriage unemployment gap, but the gap is almost entirely explained by the difference between married and single females with respect to the OU transition, as observed in table 2. Again, these results are in line with the idea that married females' attachment to the labor force is the one most mediated by the household, and that this group of the population is the one most likely to make transitions in and out of the labor force. This is not the case for single females nor males.

The simple flow decomposition exercise above shows which forces are behind the marriage unemployment gap. The fact that these forces have been operating in a relatively stable manner over our entire adjusted sample coupled with a stable downward trend in the fraction of workers choosing to marry, hints at the importance of the economic forces inside a household to explain the gap. However, to explain the existence of the marriage unemployment gap is out of the scope of this paper.

5 Conclusions

In this paper we document different patters regarding worker flows and unemployment rates between married and non-married individuals in the U.S. economy. Using monthly CPS data from 1976 to 2013, we show that the unemployment rate of married individuals is systematically lower than for singles, both for males and females. This difference is persistent over time despite the notable changes in the composition of the U.S. labor market: the increase of female labor force participation, the convergence between the participation rate of single and married females, the slight decrease of male's participation, and the dramatic decrease of the proportion of married individuals in the labor force.

We use monthly transitions across labor market states to perform a decomposition exercise that allows use to identify the main channels driving the different unemployment rates between singles and married. We find that for males, the higher employment exit probabilities exhibited by single males are the main determinant of the gap. For females, we find that the participation margin also plays a fundamental role. Importantly, we find that the contribution of these channels to the gap is stable over time.

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Appendix

A Figures of Non-adjusted data

(a) Males (b) Females

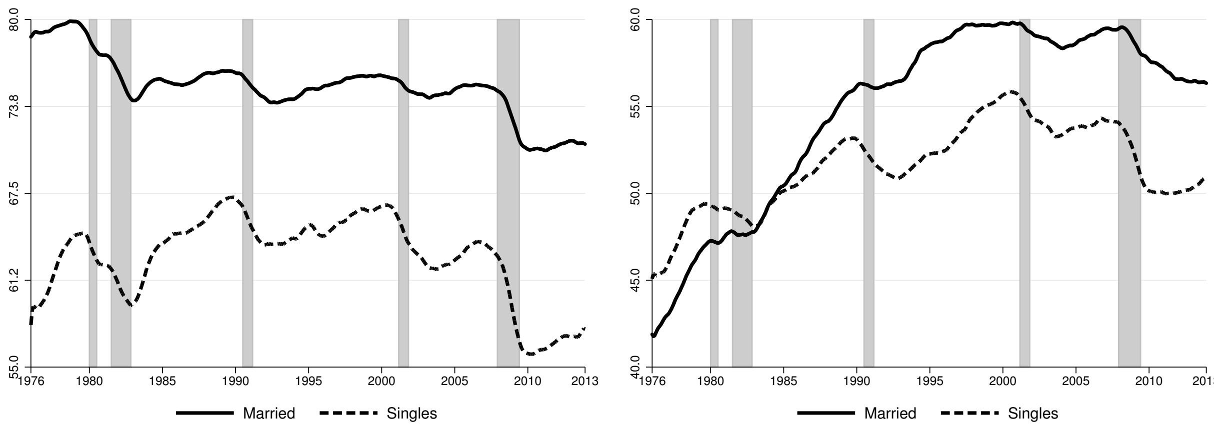

Figure 7: Employment rate by marital status. CPS 1976:1-2013:12. Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

(a) Males (b) Females

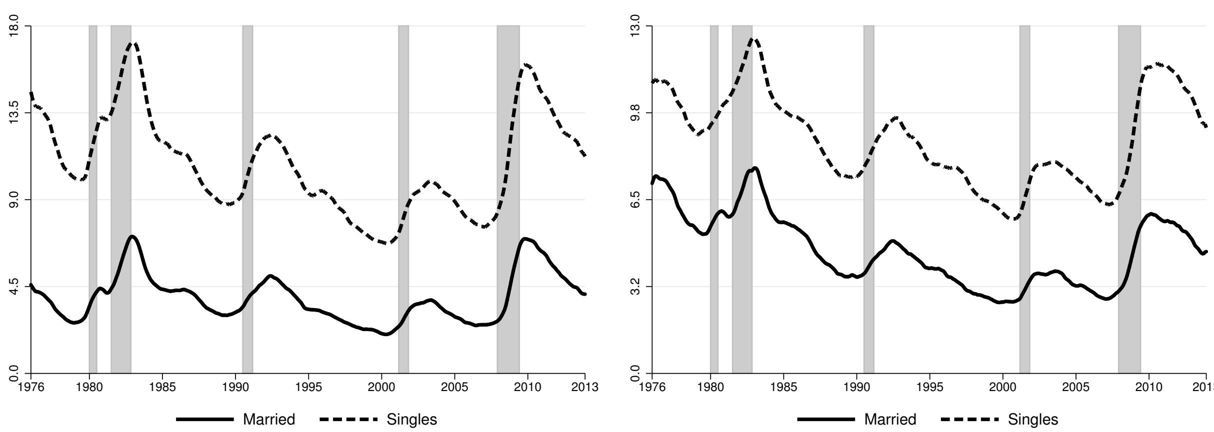

Figure 8: Unemployment rate by marital status. CPS 1976:1-2013:12. Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

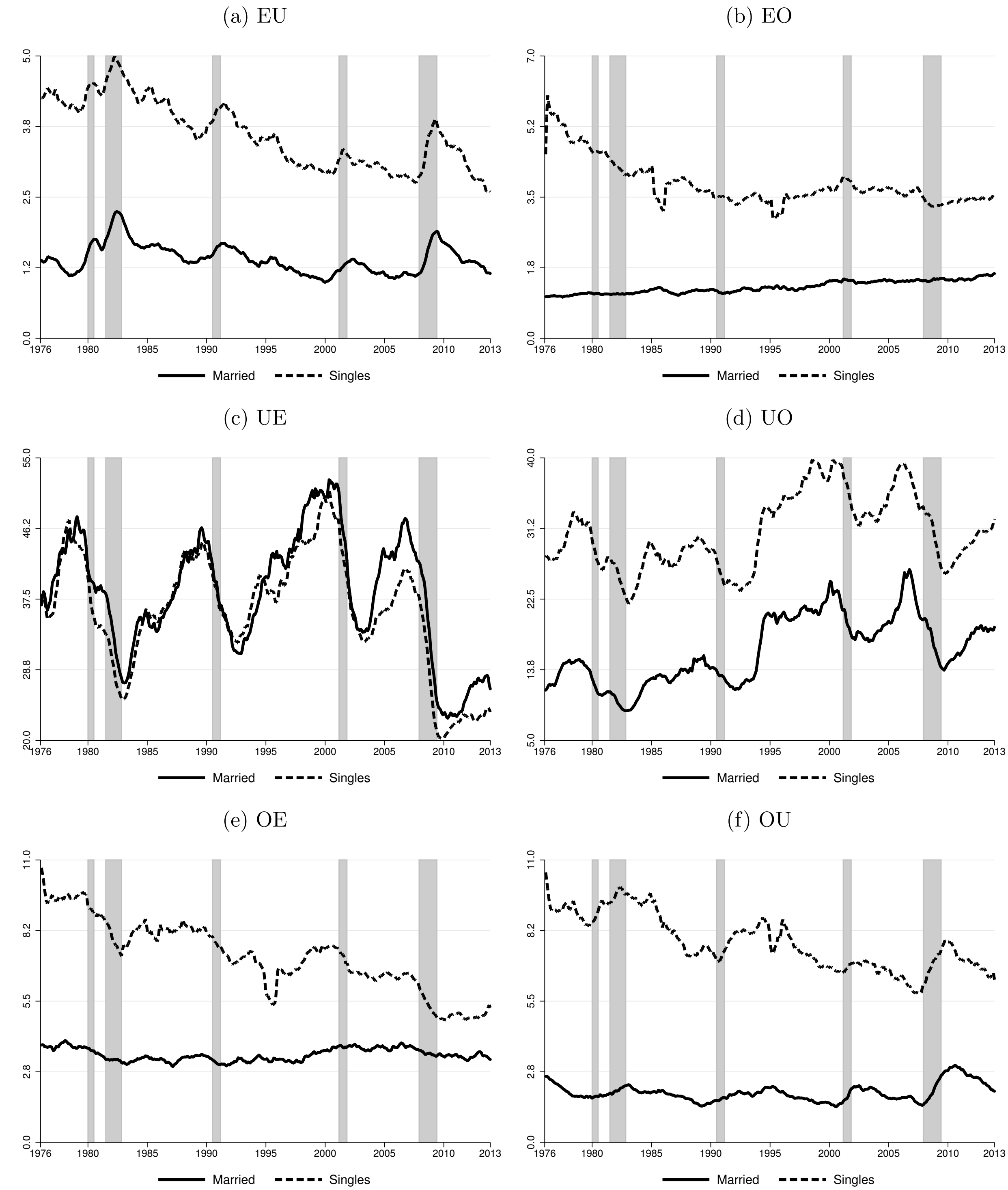

Figure 9: Labor market transitions for males. CPS 1976:2-2013:12. Corrected for time aggregation bias. Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

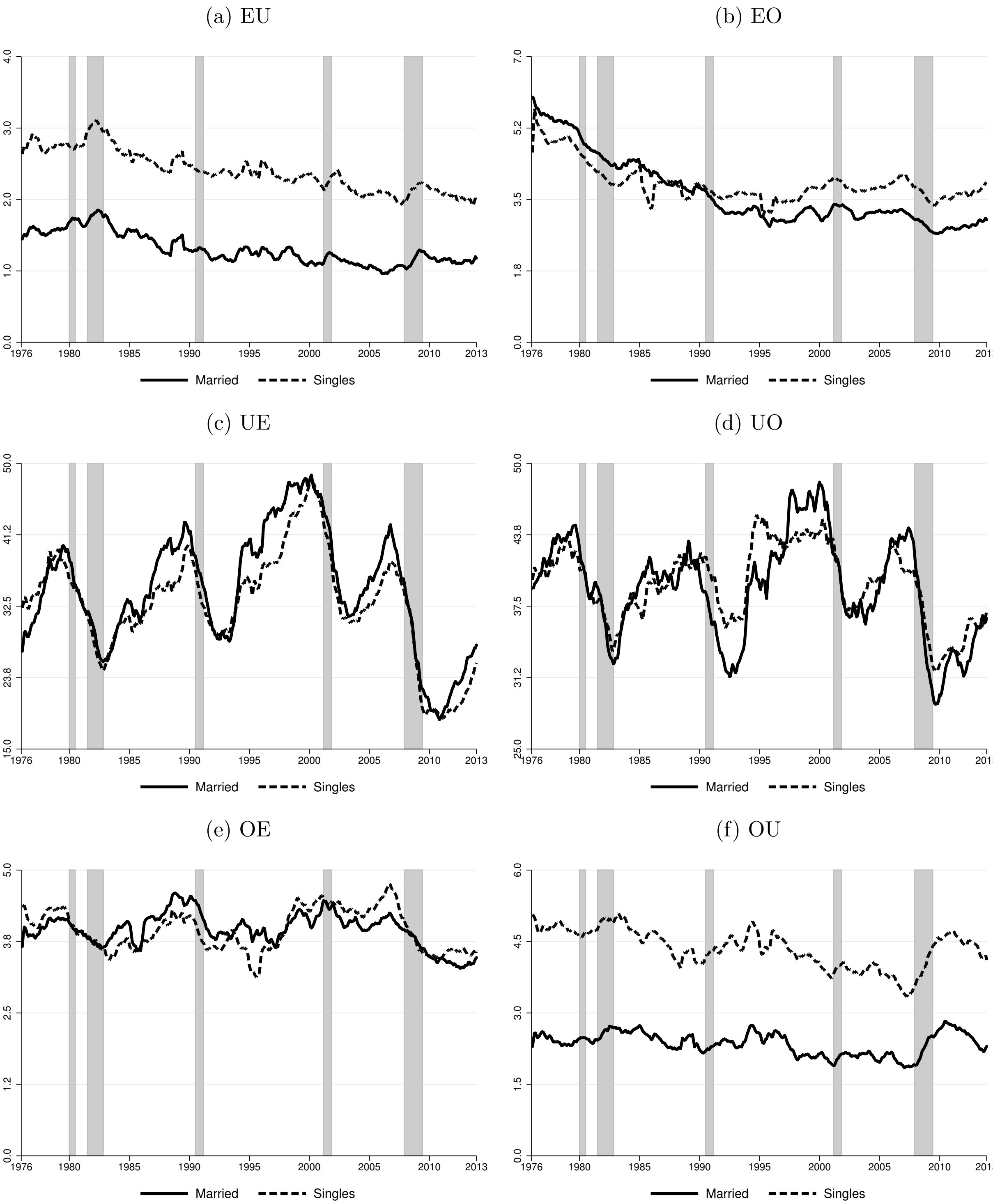

Figure 10: Labor market transitions for females. CPS 1976:2-2013:12. Corrected for time aggregation bias. Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.

B Our Method of Controlling for Observables vs. Marginal Effects Probit

In this section we compare our method to control for observables and the results from a Probit regression. Figure 11 compares the difference between the unemployment rate of single and married individuals in our artificial sample with the marginal effect of being single in the following Probit model:[7]

$$U = \Phi(\beta_0 \times single + \vec{\beta_1} \times \vec{X} + \epsilon) \tag{1}$$

where U is a dummy variable that takes value 1 if the individual is unemployed and 0 otherwise, $single$ is a dummy variable taking value 1 if the individual is not married and 0 otherwise, and the vector $\vec{X}$ is the set of observable characteristics we use in the construction of our artificial sample.

In the artificial sample, both married and single individuals present the same observable characteristics. Hence, the difference between the unemployment rate of single and married individuals reflects the different probabilities of being unemployed conditional on observables. This is equivalent to estimating the Probit model in equation 1 and computing the marginal effect of being single (or married) controlling for observables. These results indicate that, both the exact matching method we use to control for the effects of observables and using a Probit model to clean out the effects of observables, deliver similar results. We choose to use exact matching because it does not require to assume a particular parametric relationship between observables and labor market outcomes.

[7] See Section **??** for a complete description of the procedure for constructing the artificial sample.

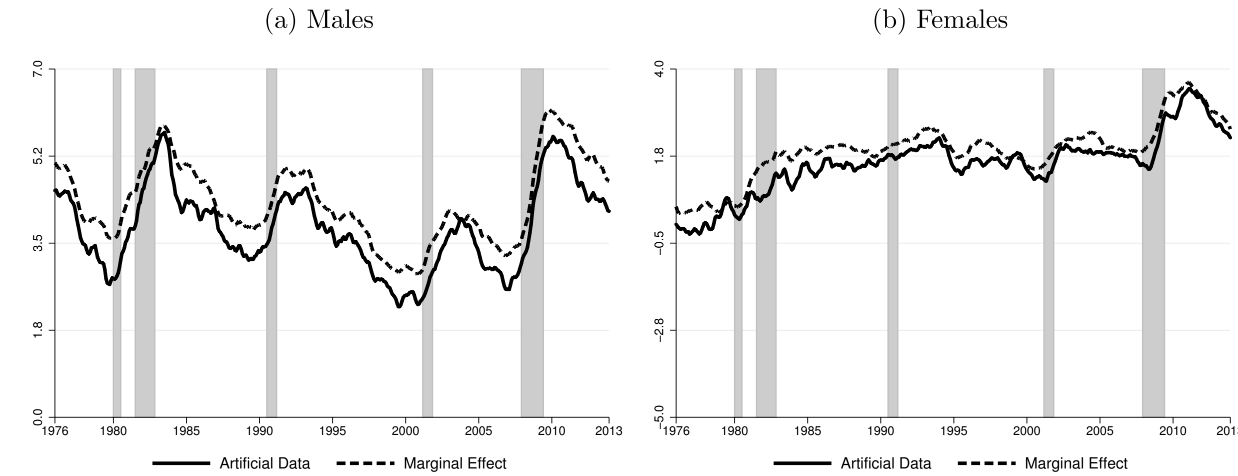

Figure 11: Unemployment rate. CPS 1976:1-2013:12. The solid line (Artificial Sample) represents the difference between the unemployment rate of single and married individuals in our artificial sample. The dashed line (Marginal Effects) is the marginal effect of being single computed from the estimation of the Probit model in equation 1. Series smoothed using a 12-month moving average. All individuals aged 16 or more. Gray bars denote NBER recession dates.