Does the Added Worker Effect Matter?*

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Abstract

The added worker effect (AWE) measures the entry of individuals into the labor force due to their partners' adverse labor market outcomes. We propose a new method to calculate the AWE that allows us to estimate its effect on any labor market outcome. The AWE reduces the fraction of households with two non-employed members by 16% for the 1977-2018 period; 28% in the 1990 recession and 23% during the great recession. The AWE also accounts for why women's employment is much less cyclical and more symmetric than men's. Without the AWE, married women's employment would be as volatile as men and display negative skewness (declining quickly in recessions and recovering slowly in expansions). In recessions, while some women lose their employment, others enter the labor market and find jobs. This keeps female employment relatively stable.

Keywords: Added Worker Effect, Household Labor Supply, Intra-Household Insurance, Female Employment, Cyclicality, Skewness.

JEL Codes: D1, E32, J21, J22

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1 Introduction

More than 60% of the US labor force between ages 25 and 54 is married.[1] The growth of two-earner households is the result of married women's entry into the labor market since the 1950s. While only 35% of married women between the ages 25 to 54 were in the labor force in 1960, today, about 74% of them are.[2] Hence, for a majority of workers, labor market decisions are made jointly with a partner. Despite the growing importance of two-earner households, the labor market outcomes are almost exclusively reported and analyzed using individual-level data.

Married-couple households, with two potential earners, can cope with labor market shocks better than single-person households. If one household member gets an adverse employment or wage shock, the other member can adjust their labor supply to compensate. Typically, the added worker effect (AWE) measures the entry of individuals into the labor force due to their partners' job loss. How much can households smooth shocks by adjusting their labor supply behavior? Pruitt and Turner (2020) document that households face substantially less earnings risk than singles. Blundell, Pistaferri, and Saporta-Eksten (2016) estimate that only about 34% of permanent shocks to male wages and 20% of permanent shocks to female wages are passed through to household consumption and that family labor supply is a key insurance channel available to households. Hence, the AWE can potentially be important.

In this paper, we propose a new method to calculate the AWE. We do this using data for the 1976-2018 period from the Current Population Survey (CPS), the main data source to study labor market dynamics in the US. We focus on joint labor market states for couples. A joint state can be, for example, both husband and wife being out of the labor force (OO) or the husband being unemployed and the wife being employed (UE). There are nine such states, which expand the standard individual labor market states of employment (E), unemployment

[1] The numbers are based on the Current Population Survey (CPS). For the 2000-2018 period, about 60% of men and 62% of women were married.

[2] There is an extensive literature that studies the rise of married female labor force participation. See recent reviews by Petrongolo and Olivetti (2016), Doepke and Tertilt (2016), and Greenwood, Guner, and Vandenbroucke (2017).

(U) and out-of-the-labor-force (O) states.

We calculate monthly transitions of husbands and wives among these nine possible labor market outcomes, a nine-by-nine transition matrix. We then shut down transitions associated to the AWE, and recalculate counterfactual joint labor market outcomes. For example, if we are calculating the AWE for women, we ignore transitions like EO to UE or UO to UE, which indicate that the husband looses his job (moves E to U) or stays unemployed (U to U), and the wife enters the labor force and finds a job (moves from O to E). Hence, our definition of the AWE considers the entry of women to labor force both due their husbands job loss and continuing unemployment.

Once we have counterfactual joint labor market outcomes for couples, we can reconstruct any labor market statistics for households or individuals. The approach combines the insight by Lundberg (1985) that the joint labor market transitions are essential to understand the AWE with the methodology by Shimer (2012) that calculates counterfactual labor market outcomes by eliminating fluctuations in particular transition(s). While Shimer (2012) replaces particular transitions with their sample mean, we set them to zero.

We find that the AWE increases the labor force participation of married women by about 2.64 percentage points for the period we study (the average labor force participation for women was 70.3%). Moreover, the AWE has been increasing. For the 2010-2017 period, the increase in female labor force participation due to the AWE is 2.87 percentage points (the average was 72.6%). We then look at how household and individual labor market outcomes would be without the AWE. For households, we focus on the fraction with two non-employed members. In the data, such households are about 3.32% of all households in the economy. In the recent recession, the number increased to around 5%. We find that in the absence of the AWE, the number of such households, on average, would be 3.72%, 0.4 percentage points larger, and would have increased to 5.55% in the recent recession.

We then ask whether the AWE affects individual labor market outcomes. We document two facts on the cyclical movements in the employment for men and women. The first fact is well known. Women's employment is less cyclical (see Doepke and Tertilt (2016), Fukui, Nakamura, and Steinsson (2018), and Albanesi (2019)). The second fact is novel. We show that men's employment shows negative skewness, i.e., they experience more significant drops in employment during recessions, followed by slow recoveries in expansions. This is also how aggregate employment behaves, as documented by Ferraro (2018). Women's employment, on the other hand, is much more symmetric across booms and recessions, exhibiting a sine-like pattern. We find that without the AWE, fluctuations in women's employment look like men's; they would have higher volatility and negative skewness. This happens because women who enter the labor force during recessions move mainly into employment. As a result, while some women lose their employment in a recession, others enter the labor force, find jobs, and keep the employment rate relatively stable. We show that these findings are robust to changes in the demographic composition of married couples during this period.

The paper is related to four strands of literature. First, the paper builds on the empirical literature on the AWE. Lundberg (1985), Stephens (2002), Juhn and Potter (2007), Halla, Schmieder, and Weber (2018), and Bredtmann, Otten, and Rulff (2018), are examples from this literature. While these papers exclusively focus on how women's labor force participation respond to job loss by their husbands, our method allows us to study the impact of the AWE on a wider set of labor market outcomes. Within this literature, Mankart and Oikonomou (2016) document that added worker effect has been growing in recent decades. Second, our paper is related to the recent macroeconomics literature that builds models with two-earner households to study how households smooth idiosyncratic income shocks. Ortigueira and Siassi (2013), Birinci (2019), Guner, Kaygusuz, and Ventura (2020), and Wu and Krueger (2021) are examples in this literature. Following Guler, Guvenen, and Violante (2012) and Flabbi and Mabli (2018), a set of papers within this literature model joint search behavior of husbands and wives was developed, e.g. Mankart and Oikonomou (2017), Pilossoph and Wee (Forthcoming), Wang (2019), Choi and Valladares-Esteban (2020), García-Pérez and Rendon (2020). Our work is also related to the papers that show that labor market fluctuations differ by gender and the implications of these differences for the aggregate economy, e.g., Albanesi and Şahin (2018), Fukui, Nakamura, and Steinsson (2018), Albanesi (2019), Ellieroth (2019), and Coskun and Dalgic (2020). We highlight one potential factor, the AWE, that can generate gender differences in labor market fluctuations. Finally, at the methodological level, we build on the empirical literature on labor market fluctuations, e.g. Blanchard, Diamond, Hall, and Murphy (1990), Fujita and Ramey (2009), Shimer (2012), and Elsby, Hobijn, and Şahin (2015).

The rest of the paper is organized as follows. In Section 2, we describe the data and introduce key concepts. Section 3 presents joint transitions. In Section 4 we calculate the AWE and in Section 5 we study its impact on household and individual labor market stocks. We conclude in Section 6.

2 Data

We use monthly data from the Outgoing Rotation Groups of the CPS. Every household (address) that enters the CPS is interviewed for four consecutive months, then is not interviewed (rotated out) for the next eight months, and interviewed again (rotated in) for four more months. This procedure implies that each month eight rotation groups are surveyed, and six of these eight groups will be surveyed again next month. As a result, it is possible to follow 3/4 of individuals and match their information between two consecutive months. We follow a standard matching procedure, specified in Shimer (2012), based on matching households with the same identification code, as long as household members' characteristics (age, sex, race and education) are consistent between two consecutive months.

Our final sample spans from February 1976 until August 2018. We use the Hodrick-Prescott (HP) filter to determine trend and cyclical components of labor market stocks. Whenever we use HP filter, we present the results for the period of 1977:Q1 to 2017:Q3, disregarding the first 5 and last 5 quarters.[3] We restrict the sample to all couples who report

[3]We do this to avoid the end-point problems associated with the HP-filter; see Giorno, Richardson,

to be married and living in the same household and also report that one of the two members of the couple is the head. To minimize the effects of schooling and retirement decisions, the sample is restricted to couples in which both members are 25 to 54 years old. These restrictions result in a sample of about 12,000 couples per month.

We extend the standard concepts of individual labor market states, employment (E), unemployment (U), and non-participation (O), to couples and consider nine different labor market states: both employed, husband employed/wife unemployed, husband employed/wife non-participant, etc. We label these states using two letters. The first letter refers to the labor market status of the husband and the second letter refers to the labor market status of the wife. For example, UO codes a couple in which the husband is unemployed (U) and the wife is non-participant (O). Any couple can be in 9 different *joint* labor market states (EE, EU, EO, UE, UU, UO, OE, OU, and OO). We exploit the fact that we can link data over consecutive months to compute the flows of couples that transit form one labor market state to another, i.e., the number of couples who transit from state ij to state kl between any consecutive months t and $t+1$ over the number of couples in state ij in month t.

We make two adjustments, that are standard in the literature, to the raw flows. First, following Elsby, Hobijn, and Şahin (2015), we correct for classification errors by identifying and correcting streams of individual labor market states with unlikely reversals between unemployment and non-participation. Consider, for example, an individual who is recorded to be out of the labor force for two consecutive months, then appears as unemployed in the third month, and is recorded again as out of the labor force in the fourth month. The recording in the third month is attributed to measurement error and the individual is re-coded as out of the labor force in that month. Second, we correct for time aggregation bias. The CPS surveys the US population once a month. As a result, transitions that occur between two consecutive surveys are not accounted for in measured flows. To correct for this bias, we follow Shimer (2012), and map the discrete flows into their continuous-time

Roseveare, and van den Noord (1995).

transition probabilities.[4] Finally, we seasonally adjust each monthly series using a 12-months moving average. However, to better visualize the data, we aggregate monthly observations into quarters.[5]

After adjusting for classification errors and time-aggregation bias, we construct Markov transition matrices for each month in our sample. We denote these 9×9 matrices by Π_t. The probability that a couple who is in state ij in a given month t transits to state kl the following month $t+1$, an element of Π_t, is denoted by $\pi_{ij,kl}$. Hence, $\pi_{EO,EE}$ is the probability that a couple is in state EO (the husband is employed and the wife is non-participant) in period t and transits to state EE (both employed) in period $t+1$. We use a similar notation to refer to the individual transitions, π^M_{ij} and π^W_{ij}, of men (M) and women (W), respectively. Finally, we use $\pi^M_{ij|kl}$ and $\pi^W_{ij|kl}$ to denote an individual transition from i to j conditional on the spouse transiting from k to l. For example, $\pi^W_{OU|EU}$ is the probability that a woman transits from O to U, conditional on the husband moving from E to U.

3 Joint Transitions

In this section, we document the joint labor market transitions of married couples. Table 1 reports the average transitions of husbands and wives conditional on the transitions of the spouses. Each 3×3 block in Table 1 shows transitions among E, U and O for husbands (the upper panel) and wives (lower panel) for a given transition of the partner.[6]

There are significant gender differences in movements across labor market states Table 1. Men are on average more attached to labor force than women. The persistence of employment for men is higher than that of women for any transition of their partners:

$$\pi^M_{EE|kl} \geq \pi^W_{EE|kl} \text{ for all } k, l.$$

[4] We provide further details on these adjustments in Appendix A.1.

[5] Figure A.3 in Appendix A.2 shows the unemployment, employment, and participation rates for married, single, and all individuals. While our focus is on married individuals, for the particular age group we consider, the labor market fluctuations for married individuals mimic very closely the aggregate movements.

[6] In Appendix A.3, we report the average of unconditional transition matrices, Π_t, for the sample period.

Men (women) are less (more) likely to transit out of labor force, independently of the transitions of their spouse:

$$\pi^M_{iO|kl} \leq \pi^W_{iO|kl} \text{ for all } i, k, l.$$

In Table 1 we also see that household members coordinate their labor supply decisions. First, we observe the *added-worker effect*, that is, the increase in labor force participation in response to the unemployment of the spouse. An out-of-the-labor-force female whose husband loses his job, i.e., moves from employment to unemployment, is twice as likely to enter the labor force, either as employed (6.38%) or unemployed (7.58%), than an out-of-the-labor-force female whose husband keeps his job (4.91% and 2.16%):

$$\pi^W_{OU|EU} + \pi^W_{OE|EU} \geq \pi^W_{OU|EE} + \pi^W_{OE|EE}.$$

Similarly, an out-of-the-labor force husband, whose wife transits from employment to unemployment, enters the labor market as employed with a probability of 10.92% and as unemployed with probability of 11.26% . This is about twice as large as if his wife remains employed (8.40% and 5.46%):

$$\pi^M_{OU|EU} + \pi^M_{OE|EU} \geq \pi^M_{OU|EE} + \pi^M_{OE|EE}.$$

Table 1: Conditional Labor Market Transitions of Married Couples

Female transitions		Male employed E	Male employed U	Male employed O	Male unemployed E	Male unemployed U	Male unemployed O	Male OLF E	Male OLF U	Male OLF O
Male employed	E	96.52	0.96	2.52	91.47	5.24	3.29	81.90	2.63	15.56
	U	32.81	41.96	25.24	25.05	54.33	20.63	34.84	37.96	37.85
	O	4.91	2.16	92.93	6.38	7.58	86.04	9.91	3.38	86.71
Male unemployed	E	94.60	2.38	3.02	96.30	1.99	1.71	94.17	3.32	2.52
	U	47.09	31.95	25.48	19.41	64.21	16.38	30.32	38.42	45.30
	O	6.02	4.86	89.12	3.66	6.92	89.42	3.62	5.25	91.12
Male OLF	E	90.93	2.15	7.00	94.55	3.78	2.03	96.41	1.34	2.25
	U	28.77	50.66	32.02	13.73	60.69	25.58	25.15	48.99	25.86
	O	25.32	6.31	68.37	6.02	15.06	79.24	2.69	1.85	95.46

Male Transitions		Female employed E	Female employed U	Female employed O	Female unemployed E	Female unemployed U	Female unemployed O	Female OLF E	Female OLF U	Female OLF O
Female employed	E	98.61	0.96	0.43	92.57	6.47	1.17	95.13	1.58	3.29
	U	31.69	59.66	8.65	31.83	59.67	8.50	49.52	42.03	12.80
	O	8.40	5.46	86.14	10.92	11.26	78.38	21.58	5.85	72.57
Female unemployed	E	96.89	2.30	0.84	96.93	2.50	0.57	96.74	2.41	0.90
	U	47.60	43.24	8.90	21.30	73.99	4.71	30.03	53.06	19.98
	O	12.23	9.26	78.51	6.29	7.25	86.46	8.87	8.84	82.29
Female OLF	E	96.44	1.77	1.79	95.85	3.57	0.59	98.37	1.06	0.57
	U	46.96	43.93	13.76	21.57	71.77	6.67	35.34	54.68	9.98
	O	54.20	7.96	39.56	12.39	21.60	66.67	6.94	3.79	89.27

NOTE: CPS 1976:Q1 to 2018:Q3. All individuals aged 25-54. The upper panel shows the transition probability of wives across E–Employment, U–Unemployment, and O–Non-participation conditional on her husband's transition from the state in the row to the state in the column. The lower panel shows the same for males. Estimates are adjusted for classification errors, time aggregation, and seasonality (12-months moving average).

Second, we observe *joint movers*. The conditional probability of a particular transition is the highest if one's partner also experiences the same transition. Hence, for any transition ij:

$$\pi^W_{ij|ij} \geq \pi^W_{ij|kl} \text{ and } \pi^M_{ij|ij} \geq \pi^M_{ij|kl} \text{ for all } k, l.$$

Consider what happens to a woman whose husband transits from employment to unemployment (E to U). The probability that the wife also transits from employment to unemployment is 5.24%. This probability is larger than the corresponding E to U probability for any other transition of the man. If the husband stays on the job, for example, this probability is just around 1%, and it is 3.78% when the husband moves from O to U. This 5.24% probability is also 5 times higher than the unconditional probability of females transiting from E to U (1.05%). We observe a similar pattern for husbands. The probability of a husband to move from E to U is the highest when his wife also moves from E to U.

The AWE and joint moves can have opposite effects on female employment. In a recession, for example, the AWE mitigates the decline in female employment. Women whose husbands lost their jobs enter the labor force, and some of them find jobs. On the other hand, others whose husbands become unemployed might choose to move from employment to unemployment. Such joint moves can be triggered, for example, by joint search in different labor markets. In contrast to the AWE, these joint moves will lower the aggregate female employment.

4 The Added Worker Effect

In this section, we propose a new way to measure added worker effect. We follow Lundberg (1985), and focus on joint transitions. Consider those transitions in which one partner moves from employment to unemployment or remains unemployed, and the other partner enters the labor force and becomes employed or unemployed. If the wife is the one entering the labor force, these transitions are: EO to UE, UO to UE, EO to UU, and UO to UU. If the husband is the added worker, the relevant transitions are: OE to EU, OU to EU, OE to UU, and OU to UU. Each of these moves represents the entry of a partner to the labor force to mitigate the other partner's negative labor market outcomes. The partner that enters the labor force is either looking for a job, a movement from O to U, or has already found one, a move from O to E. We measure the added worker effect as the change in labor market outcomes that results when these transition probabilities are set to zero.

To compute the effect of the added worker effect on the labor market states, we build on the methodology in Shimer (2012). In calculating the effects of the AWE, we focus on unemployment, (U/L), employment, (E/P) and participation (L/P) rates where L is the total labor force, $L = E + U$, and P is total population, $P = L + O$.

First, for each month in our sample, we use the matrix of joint transition probabilities calculated from the data, Π_t to compute the steady state distribution over the 9 joint labor market stocks associated to these transitions. Let s_{ij} be the fraction of couples in state ij at time t. Between t and $t+1$, some couples move from other states to ij, while some couples in ij transit to other states. In the steady state these inflows and outflows have to cancel each out:

$$\underbrace{\left(\sum_{k \neq i, l \neq j} \pi_{ij,kl}\right) s_{ij}}_{\text{outflows}} = \underbrace{\sum_{k \neq i, l \neq j} \pi_{kl,ij} s_{kl}}_{\text{inflows}}. \tag{1}$$

Given that we compute the transition probabilities $\pi_{ij,kl}$ from the data, Equation 1 is a system of 9 equations and 9 unknown s_{ij} values. If the s_{ij} values computed from equation (1) are close to the ones in the data, Equation (1) provides a natural way to calculate the AWE, since we can replace any $\pi_{kl,ij}$ value with an alternative and recalculate s_{ij} values.[7]

In the second step, we replace all the AWE transitions with the transitions in which women (or men) do not react to their partners' job loss or continuing unemployment. To calculate the AWE for women, for example, we set:

$$\pi^{noAWE}_{EO,UE} = \pi^{noAWE}_{UO,UE} = \pi^{noAWE}_{EO,UU} = \pi^{noAWE}_{UO,UU} = 0,$$

and add then transitions to

$$\pi^{noAWE}_{EO,UO} = \pi_{EO,UO} + \pi_{EO,UE} + \pi_{EO,UU},$$

and

$$\pi^{noAWE}_{UO,UO} = \pi_{UO,UO} + \pi_{UO,UE} + \pi_{UO,UU}.$$

[7]Figure B.1 in Appendix B.1 shows the data on joint stocks together with the stocks implied by Equation (1).

We can also present this procedure in terms of conditional transitions for $g = \{M, W\}$ as:

$$\pi_{OE|EU}^{g^{noAWE}} = \pi_{OU|EU}^{g^{noAWE}} = \pi_{OE|UU}^{g^{noAWE}} = \pi_{OU|UU}^{g^{noAWE}} = 0,$$

with

$$\pi_{OO|EU}^{g^{noAWE}} = \pi_{OO|EU}^{g} + \pi_{OE|EU}^{g} + \pi_{OU|EU}^{g},$$

and

$$\pi_{OO|UU}^{g^{noAWE}} = \pi_{OO|UU}^{g} + \pi_{OE|UU}^{g} + \pi_{OU|UU}^{g}.$$

We recalculate joint outcomes for this counterfactual economy from equation (1), and denote them by s_{ij}^{noAWE}. Then, we can aggregate s_{ij} and s_{ij}^{noAWE} into *individual* labor market stocks (E, U, and P) and (E^{noAWE}, U^{noAWE}, and P^{noAWE}), and calculate the differences. The procedure is flexible and can be used to compute how the added worker affects any other labor market outcome.

The existing measures of the AWE focus exclusively on the entry of women into the labor force which is associated to the job loss of their husbands. Our method can be used to compute not only the change in participation, but also how the added worker affects any other labor market outcome.

Table 2 documents the contribution of the added worker effect. For the entire period (1977-2017), the added worker effect increases female labor force participation by about 2.64 percentage points. Most of this increase is due to higher employment. Without the AWE, the employment rate of married women would be 2.42 percentage points lower. Moreover, the importance of the AWE has been increasing in recent decades. For the 2000-2010 and 2010-2017 periods, the labor force participation rates of women are higher by 3.08 and 2.87 percentage points, respectively. The effect of the added workers on unemployment is not negligible either. In the absence of the added worker effect, the female unemployment rate would be about 0.21 percentage points lower for the 2010-2017 period (the unemployment rate of women during this period was 4.03%).[8]

Table 2: Added Worker Effect, Individuals

	1977-2017	1980-1990	1990-2000	2000-2010	2010-2017
All					
Participation Rate	1.82	1.70	1.69	2.11	2.07
Employment Rate	1.68	1.63	1.65	1.98	1.73
Unemployment Rate	0.11	0.05	-0.00	0.08	0.30
Males					
Participation Rate	0.98	0.71	1.00	1.18	1.25
Employment Rate	0.96	0.90	1.05	1.14	0.94
Unemployment Rate	-0.01	-0.22	-0.08	0.00	0.28
Females					
Participation Rate	2.64	2.64	2.30	3.08	2.87
Employment Rate	2.42	2.34	2.20	2.91	2.59
Unemployment Rate	0.18	0.29	0.04	0.08	0.21

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent differences between the means of the data and the counterfactual experiment calculations (in which the added worker effect is shut down) in percentage points, for different time periods. In the upper panel we shut down all transitions mentioned above (the added worker effect for males and females). In the middle panel we shut down transitions corresponding to males' added worker effect: OE to EU, OU to EU, OE to UU, and OU to UU. In the lower panel we shut down the joint transitions, corresponding to females' added worker effect: EO to UE, UO to UE, EO to UU, and UO to UU.

Although the existing papers on the AWE concentrate on how much the labor force participation of wives changes as a result of their husbands' job loss, our analysis reveals that there also exists a small added-worker effect for husbands, which has also been increasing in recent decades. For the 2010-2017 period, due to the AWE, the participation of men increases by 1.25 percentage points (the participation rate of men during this period was 93.61%). While for women almost all the increase in participation is absorbed by employment, for men about 22% of the increase in labor force participation results in higher unemployment.[9]

[8]Figure B.2 in Appendix B presents the AWE as the difference between the data and the counterfactual series for unemployment, employment, and participation rates.

[9]Table B.1 in Appendix B presents the effects of the AWE during recessions and expansions. The AWE is slightly more important for employment during recessions, while it is more important for unemployment in expansions. For unemployment, male's added worker effect is negative during recessions. This happens due to the fact that less women lose their jobs during recessions and men are still more likely to be employed than women. As a result, men enter unemployment mostly from employment, not from non-participation.

4.1 Robustness

The results are robust to alternative ways of calculating the AWE. First, the existing papers on the AWE concentrate on how much the labor force participation of wives changes due to their husbands' job loss, i.e., focus on EO to UE and EO to UE moves. This is a more conservative measure than ours since we also consider UO to UE and UO to UU movements where wives enter the labor force due to their husbands' continuing unemployment. We present the results that exclusively focus on job losses of partners in Appendix C. Not surprisingly, the AWE has a smaller impact on the female labor force participation with this calculation (1.78 vs. 2.64).

Second, in our calculations, we replace the AWE transitions with zero and assume that the wife (or husband) stays in her (or his) state. For example, $\pi_{EO,UE}$ is set to zero, and this probability is added to $\pi_{EO,UO}$. An alternative would be to replace $\pi_{EO,UE}$ not with zero but with $\pi_{EO,EE}$. This alternative assumes that some women move from O to E even if their husbands stay employed and transitions beyond that are considered as part of the AWE. The results with this alternative specification are presented in Appendix D. The AWE increases the married female labor force participation by 2.12, instead of 2.64.

Finally, during the 1976-2018 period, the US population has changed along several dimensions, such as educational attainment, age, state of residence, race, and the presence of children. We recalculate the AWE, assuming that the population's demographic composition did not change since the 1976-1979 period. We find that among these demographic characteristics, only educational attainment had a significant impact on the labor market outcomes. If the share of the population with a college degree remained in its 1976-1979 value, the impact of the AWE on female labor force participation would be even higher, 3.26 percentage point, instead of 2.64. The changes in the number of children have a similar effect. The detailed results are presented in Appendix E.

5 Why does the AWE Matter?

In this section, we study how the AWE affects the labor market stocks of households and individuals. We start with households. Since 1976, US households have changed dramatically. There has been a significant decline in the number of traditional households who are in the EO state with a breadwinner husband and a housekeeper wife. In 1976, about 45% of households had an employed husband and an out-of-labor-force wife. By the end of the sample in 2018, less than 25% of married couples consist of such traditional households. As women entered the labor force, these traditional households were replaced by households in which both members work. The fraction of such households increased by more than 20 percentage points, from 44% to 67%, between 1976 and 2018. The increase was remarkable until the late 1990s. Since then, the fraction of households with two employed individuals declined slightly, from about 69% to 67%. The decline was matched with an increase in households in which men are out of the labor force (OE, OU and OO states) and coincides with the decline in aggregate labor force participation.[10] There has also been an increase in the number of households where the traditional roles of husbands and wives are reversed. The fraction of such households, where the husband is out of the labor force and the wife is employed increased from 1.68% to 3.55% between 1976 and 2018.

These changes imply that for a majority of workers labor market decisions are not made in isolation, but together with a partner. Yet, the labor market stocks are almost exclusively reported and analyzed using individual-level data. While the Bureau of Labor Statistics (BLS) reports employment characteristics of families, e.g., fraction of families with at least one employed or at least one unemployed member, these statistics do not receive much attention.[11]

The AWE allows households to smooth adverse labor market shocks. When one partner loses their job, the other enters the labor market so that at least one member has a job. As

[10] For an analysis of the decline in the US labor force, see, among others, Barnichon and Figura (2015) and Krueger (2017)

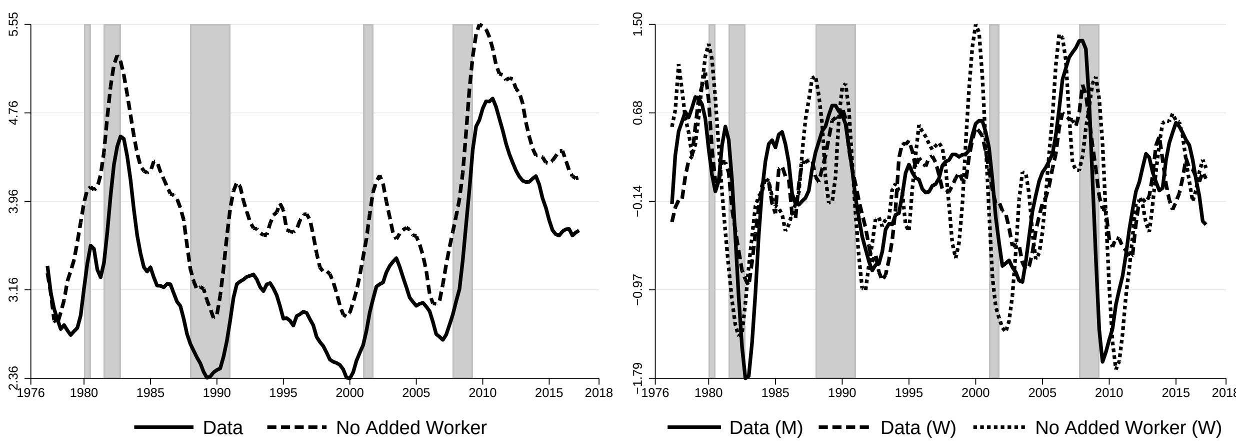
[11] `https://www.bls.gov/news.release/famee.toc.htm`

a result, the fraction of households with "two non-employed members" is a natural metric to evaluate the impact of the AWE. The solid line in Figure 1a shows the fraction of such households, i.e., households in states UU, UO, OU, and OO. Between 1976 and 2018, 3.32% of all married households have two non-employed members. In the recent recession, the number was close to 5%. The dashed line in Figure 1a shows what would be the fraction of such households without AWE. The average share of households with both members non-employed in the absence of the AWE is about 3.72%. Hence, without the AWE, the fraction of households without any employed members would be 0.4 percentage points higher. This is about 16% of households without any employed members. We see this measure as a conservative indicator of how the AWE helps households to smooth shocks since it abstracts from adjustments along the intensive margin.[12]

Figure 1: Added Worker Effect, Households

(a) Share of households with both members non-employed

(b) Cyclical component of employment



NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. In the panel 1a, the solid line represents the share of households with two non-employed members. The dashed line represent the results of counterfactual experiments in which we shut down added-worker effect in the economy. In the panel 1b, the solid line represents cyclical component of men's employment, the dashed line represents the cyclical component of women's employment, and the dotted line represents the cyclical component of the counterfactual women's employment rate in the economy with the added worker effect shut down. Monthly series smoothed using a 12-month moving average, adjusted for classification errors, corrected for time aggregation bias, HP-filtered with a smoothing parameter 1600 and presented averaged across quarters. Grey areas represent NBER recession periods.

[12]The results in Figure1 are robust to different specifications we consider in section 4.1. See Appendix C, D and E.

5.1 Individuals: Women vs. Men

In this section, we study how the AWE affects individual labor market stocks. We focus on employment and document two key differences between men and women with respect to the cyclicality of employment. The first fact is well known: women's employment is much less cyclical.[13] Figure 1b shows the cyclical component of employment for men and women, where the trend is filtered using a Hodrick-Prescott filter with a smoothing parameter 1600.

Following Doepke and Tertilt (2016), we distinguish between two measures of volatility: (i) Total volatility, measured as the standard deviation of the cyclical component of a variable; (ii) Cyclical volatility, measured as the standard deviation of a predicted variable obtained from regressing the cyclical part of that variable on the real GDP's cyclical component. As an alternative measure of cyclical volatility, we also report the ratio of the standard deviation of the cyclical component of a series to that of real GDP. The first column in Table 3 shows the total volatility of participation, employment, and unemployment, for males and females, while the second and third columns report cyclical volatility. Female employment is much less volatile than male employment (0.43 vs. 0.64). The differences in cyclical volatility in columns 2 is even larger, 0.25 vs. 0.48 .

Next, we show that men and women also differ in the asymmetry (or skewness) of their employment fluctuations. For asymmetry, we follow Sichel (1993) and Ferraro (2018) and report two measures. The first is the skewness in levels, which measures the asymmetry of the cyclical component of a series. If a series has zero skewness in levels, then it goes up and down in a symmetric manner in recessions and expansions, generating a sine-like pattern, with the same magnitudes of peaks and troughs. The second measure is the skewness in growth rates, which measures the asymmetry in the behavior og growth rates. If a series has zero skewness in growth rates, expansions and recessions are associated with similar growth

[13] See Fukui, Nakamura, and Steinsson (2018) and Albanesi (2019).

rates of the opposite sign. For both measures, the skewness of a series is measured by the coefficient of skewness, given by $skew(x) = \mathbb{E}[(x_t - \mathbb{E}[x_t])^3]/\sigma_x^3$.

The upper panel of Table 3 shows the results (p-values are reported in brackets). Employment is negatively skewed for men (skewness in levels is -0.60 and skewness in growth rate is -1.21). Hence men experience more significant drops in employment during recessions, followed by slow recoveries in expansions. The aggregate employment also shows negative skewness, that is the fact documented by Ferraro (2018). This is, however, not the case for women. Women' employment behavior is symmetric in levels (skewness is, basically, zero).

In terms of skewness in growth rates, women's employment grows marginally faster than it falls (skewness in growth rates is 0.4). Unemployment displays positive skewness in levels, i.e., peaks in recessions are larger than troughs during expansions. The skewness in levels is, however, almost twice as high for men as it is for women (0.81 vs. 0.49). The pattern also emerges in growth rates (1.33 vs. 0.64). If we look at the participation rate for men and women, the troughs and peaks in levels are symmetric. However, the participation of women grows faster in recessions than it falls in expansions (steepness skewness is 0.4).

The lower panel of Table 3 shows the cyclical properties of employment without the AWE. In the absence of the AWE, women's employment is similar to men's: both in terms of volatility and skewness (see also Figure 1b). The AWE has almost no effects on the volatility of men's employment. In contrast, without the AWE, the volatility of women's employment is much higher than in the data (0.71 vs. 0.43) and close to the volatility of men's employment. The AWE also has a significant impact on the skewness of women's employment. In a world without the AWE, the cyclical behavior of women's employment would look like men's employment, with significant and fast declines in recessions and slow recoveries in expansions. The skewness would be negative both in deepness (-0.30) and in steepness (-0.41).[14]

[14]The results in Table 3 are robust to different specifications we consider in section 4.1. See Appendix C, D and E.

Table 3: Added Worker Effect, Volatility and Skewness

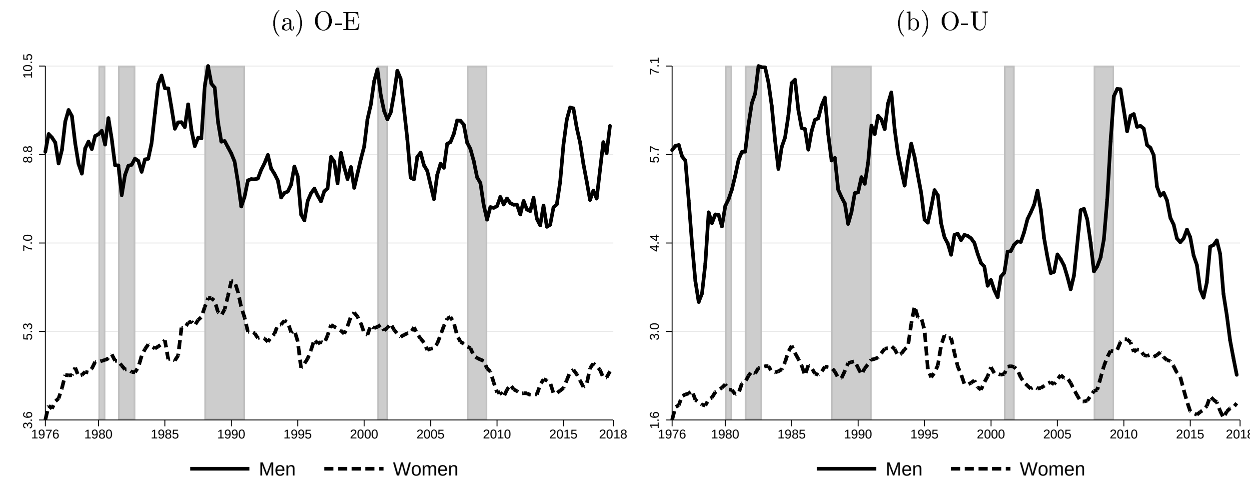
	Volatility	Cyclical Volatility	SD/SD_{GDP}	Skewness in levels	Skewness in growth rates
			Men		
Participation	0.11	0.03	0.07	-0.12	0.18
				[0.516]	[0.338]
Employment	0.64	0.48	0.41	-0.61	-1.21
				[0.002]	[0.000]
Unemployment	0.62	0.48	0.40	0.81	1.33
				[0.000]	[0.000]
			Women		
Participation	0.24	0.02	0.16	-0.07	0.40
				[0.717]	[0.036]
Employment	0.43	0.25	0.27	-0.09	0.40
				[0.634]	[0.038]
Unemployment	0.45	0.34	0.29	0.49	0.64
				[0.012]	[0.001]
			Without the added-worker effect		
			Women		
Participation	0.56	0.15	0.36	0.07	-0.35
				[0.709]	[0.066]
Employment	0.71	0.34	0.45	-0.30	-0.41
				[0.108]	[0.033]
Unemployment	0.42	0.32	0.27	0.27	0.58
				[0.155]	[0.003]

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent standard deviations of the cyclical component, standard deviation of the predicted values of labor market states from the regression of cyclical component of labor state on cyclical component of log-GDP, ratios of standard deviations of the cyclical component of labor market state and cyclical component of GDP, skewness of cyclical component after HP-filtering ("in levels"), and skewness of the growth rates in the data and in the counterfactual steady state of the economy without an added-worker effect. P-values in brackets.

Why does women's employment without the AWE look like men's employment? This happens as women who enter the labor force during recessions move mainly into employment. As a result, as some women lose their employment in a recession, others enter the labor force, find jobs, and keep the employment rate relatively stable. This is further highlighted in Figure 2, which shows O to E and O to U transitions for men and women. First, while O to E

transition declines for men in each recession, O to E transition remains relatively stable for women, except in the recent downturn. Indeed such transitions increased for women in the 1990 recession. Furthermore, O to U transitions, which increase significantly for men in each recession, are also much more stable for women.

Figure 2: Individual Labor Market Transitions



NOTE: CPS 1976:Q1 to 2018:Q3. All individuals aged 25-54. Adjusted for classification errors and time aggregation bias. Seasonally adjusted using a 12-month moving average. Quarterly average of monthly data. Each transition is denoted $X - Y$, where X corresponds to the state in period t and Y – to the state in period $t+1$. X and Y can stand for: E– Employment, U–Unemployment, O–Non-participation. Grey areas represent NBER recession periods.

6 Conclusions

We propose a new method to measure the added worker effect based on the joint transitions of married households across labor market states. The method offers a transparent procedure to assess the importance of the added worker effect on any labor market outcome.

We document two key facts. First, the share of households in which both members are non-employed would be, on average, around 16% higher in the absence of the added worker effect. This measure is indicative of one of the dimensions in which the added worker effect provides insurance against negative labor market shocks. Second, we show that the differences in the cyclicality of employment between married men and women, both in terms of volatility and skewness, are driven by the added worker effect. In the absence of the added worker effect, the employment of married women would be as volatile as that of men and display negative skewness (declining sharply in recessions and recover slowly in expansions).

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Online Appendix

Appendix A: Data

A.1 Data Correction Details

A.1.1 Classification Errors

In this section of the Appendix, we provide details on adjustments for classification errors and time aggregation bias. Classification errors occur due to erroneous codification and/or misclassification of workers who are unemployed or out of the labor force. Abowd and Zellner (1985) and Poterba and Summers (1986) document that the measured transitions between unemployment and out of the labor force can be affected by such classification errors. In order to address this issue, we use the methodology proposed by Elsby, Hobijn, and Şahin (2015) which identifies and corrects streams of labor market states with unlikely reversals between unemployment and non-participation. As an example, consider an individual who is recorded to be out of the labor force for two consecutive months, then appears as unemployed in the third month, and is recorded again as out of the labor force in the fourth month. Elsby, Hobijn, and Şahin (2015) consider the recording in the third month as an error, and re-code the state of this individual as being out of the labor force for four consecutive months. Using this approach, we identify all reversal transitions between unemployment (U) and non-participation (O), such as: $O - U - O$ and $U - O - U$, and re-code them. In Table A.1 we report all the transitions that are re-coded. The difference between the two estimates is not large (with the exception of the state in which both members of the household are out of the labor force). Elsby, Hobijn, and Şahin (2015) note that this happens since there are approximately the equal number of re-coding of unemployment into non-participation and non-participation into unemployment and thus in cross-section these errors cancel each other. The classification errors, however, matter more for the transitions as documented in

Figure A.1 (men) and Figure A.2 (women).

Table A.1: Recoding of unemployment – non-participation reversals

Data	Correction	Data	Correction
OOUO	OOOO	UUOU	UUUU
OUOO	OOOO	UOUU	UUUU
EOUO	EOOO	EUOU	EUUU
OUOE	OOOE	UOUE	UUUE
.OUO	.OOO	.UOU	.UUU
OUO.	OOO.	UOU.	UUU.
Not Corrected			
OUOU	OUOU	UOUO	UOUO

NOTE: E corresponds to Employment, U–to Unemployment, O–to Non-participation.

A.1.2 Time Aggregation Bias

Time aggregation bias, which only affects transitions, is a consequence of the frequency in which the data is collected by the CPS. The CPS surveys the US population once a month. However, changes in labor market status can occur at any point in time between two surveys. Hence, if more than one transitions occur between two surveys, those would not be reflected in the *raw* flows. A simple example would be a worker who is employed at time t, then loses her job, i.e., transits from employment to unemployment, and before the next survey, finds a new job, transiting back from unemployment to employment. At time $t+1$, the worker would be recorded as being employed and, thus, her transition into unemployment and back to employment would not be taken into account. To address this problem, we follow Shimer (2012) and map the discrete flows (adjusted for the classification errors) into their continuous-time transition probabilities.

Let Γ_t be the discrete Markov transition matrix across nine possible labor market states that we calculate directly from the data and adjust for the classification errors, and let Π_t be its continuous-time counterpart. Since both continuous and discrete time transitions must generate the same steady state stocks, one can infer Π_t from Γ_t.[15]

[15] Describing the procedure below, we closely follow working paper version of Elsby, Hobijn, and Şahin

Let $s_t = (EE, EU, EO, UE, UU, EO, OE, OU, OO)$ be the probability distribution over 9 possible joint labor states. Then, $s_t = \Gamma_t s_{t-1}$, i.e.

$$\underbrace{\begin{pmatrix} EE \\ EU \\ EO \\ UE \\ UU \\ UO \\ OE \\ OU \\ OO \end{pmatrix}_t}_{s_t} = \underbrace{\begin{pmatrix}
\gamma_{EE}^{EE} & \gamma_{EU}^{EE} & \gamma_{EO}^{EE} & \gamma_{UE}^{EE} & \gamma_{UU}^{EE} & \gamma_{UO}^{EE} & \gamma_{OE}^{EE} & \gamma_{OU}^{EE} & \gamma_{OO}^{EE} \\
\gamma_{EE}^{EU} & \gamma_{EU}^{EU} & \gamma_{EO}^{EU} & \gamma_{UE}^{EU} & \gamma_{UU}^{EU} & \gamma_{UO}^{EU} & \gamma_{OE}^{EU} & \gamma_{OU}^{EU} & \gamma_{OO}^{EU} \\
\gamma_{EE}^{EO} & \gamma_{EU}^{EO} & \gamma_{EO}^{EO} & \gamma_{UE}^{EO} & \gamma_{UU}^{EO} & \gamma_{UO}^{EO} & \gamma_{OE}^{EO} & \gamma_{OU}^{EO} & \gamma_{OO}^{EO} \\
\gamma_{EE}^{UE} & \gamma_{EU}^{UE} & \gamma_{EO}^{UE} & \gamma_{UE}^{UE} & \gamma_{UU}^{UE} & \gamma_{UO}^{UE} & \gamma_{OE}^{UE} & \gamma_{OU}^{UE} & \gamma_{OO}^{UE} \\
\gamma_{EE}^{UU} & \gamma_{EU}^{UU} & \gamma_{EO}^{UU} & \gamma_{UE}^{UU} & \gamma_{UU}^{UU} & \gamma_{UO}^{UU} & \gamma_{OE}^{UU} & \gamma_{OU}^{UU} & \gamma_{OO}^{UU} \\
\gamma_{EE}^{UO} & \gamma_{EU}^{UO} & \gamma_{EO}^{UO} & \gamma_{UE}^{UO} & \gamma_{UU}^{UO} & \gamma_{UO}^{UO} & \gamma_{OE}^{UO} & \gamma_{OU}^{UO} & \gamma_{OO}^{UO} \\
\gamma_{EE}^{OE} & \gamma_{EU}^{OE} & \gamma_{EO}^{OE} & \gamma_{UE}^{OE} & \gamma_{UU}^{OE} & \gamma_{UO}^{OE} & \gamma_{OE}^{OE} & \gamma_{OU}^{OE} & \gamma_{OO}^{OE} \\
\gamma_{EE}^{OU} & \gamma_{EU}^{OU} & \gamma_{EO}^{OU} & \gamma_{UE}^{OU} & \gamma_{UU}^{OU} & \gamma_{UO}^{OU} & \gamma_{OE}^{OU} & \gamma_{OU}^{OU} & \gamma_{OO}^{OU} \\
\gamma_{EE}^{OO} & \gamma_{EU}^{OO} & \gamma_{EO}^{OO} & \gamma_{UE}^{OO} & \gamma_{UU}^{OO} & \gamma_{UO}^{OO} & \gamma_{OE}^{OO} & \gamma_{OU}^{OO} & \gamma_{OO}^{OO}
\end{pmatrix}_t}_{\Gamma_t} \times \underbrace{\begin{pmatrix} EE \\ EU \\ EO \\ UE \\ UU \\ UO \\ OE \\ OU \\ OO \end{pmatrix}_{t-1}}_{s_{t-1}}$$

where γ_i^j denotes probability of transition from the state i to the state j, and

$$\gamma_i^i = 1 - \sum_{i \neq j} \gamma_i^j.$$

Taking into account that $p_{EE} + p_{EU} + p_{EO} + p_{UE} + p_{UU} + p_{UO} + p_{OE} + p_{OU} + p_{OO} = 1$, we can rewrite the system in a following way (substituting OO state):

(2015).

$$
\underbrace{\begin{pmatrix} EE \\ EU \\ EO \\ UE \\ UU \\ UO \\ OE \\ OU \end{pmatrix}_t}_{s_t} = \underbrace{\begin{pmatrix}
\gamma^{EE}_{EE}-\gamma^{EE}_{OO} & \gamma^{EE}_{EU}-\gamma^{EE}_{OO} & \gamma^{EE}_{EO}-\gamma^{EE}_{OO} & \gamma^{EE}_{UE}-\gamma^{EE}_{OO} & \gamma^{EE}_{UU}-\gamma^{EE}_{OO} & \gamma^{EE}_{UO}-\gamma^{EE}_{OO} & \gamma^{EE}_{OE}-\gamma^{EE}_{OO} & \gamma^{EE}_{OU}-\gamma^{EE}_{OO} \\
\gamma^{EU}_{EE}-\gamma^{EU}_{OO} & \gamma^{EU}_{EU}-\gamma^{EU}_{OO} & \gamma^{EU}_{EO}-\gamma^{EU}_{OO} & \gamma^{EU}_{UE}-\gamma^{EU}_{OO} & \gamma^{EU}_{UU}-\gamma^{EU}_{OO} & \gamma^{EU}_{UO}-\gamma^{EU}_{OO} & \gamma^{EU}_{OE}-\gamma^{EU}_{OO} & \gamma^{EU}_{OU}-\gamma^{EU}_{OO} \\
\gamma^{EO}_{EE}-\gamma^{EO}_{OO} & \gamma^{EO}_{EU}-\gamma^{EO}_{OO} & \gamma^{EO}_{EO}-\gamma^{EO}_{OO} & \gamma^{EO}_{UE}-\gamma^{EO}_{OO} & \gamma^{EO}_{UU}-\gamma^{EO}_{OO} & \gamma^{EO}_{UO}-\gamma^{EO}_{OO} & \gamma^{EO}_{OE}-\gamma^{EO}_{OO} & \gamma^{EO}_{OU}-\gamma^{EO}_{OO} \\
\gamma^{UE}_{EE}-\gamma^{UE}_{OO} & \gamma^{UE}_{EU}-\gamma^{UE}_{OO} & \gamma^{UE}_{EO}-\gamma^{UE}_{OO} & \gamma^{UE}_{UE}-\gamma^{UE}_{OO} & \gamma^{UE}_{UU}-\gamma^{UE}_{OO} & \gamma^{UE}_{UO}-\gamma^{UE}_{OO} & \gamma^{UE}_{OE}-\gamma^{UE}_{OO} & \gamma^{UE}_{OU}-\gamma^{UE}_{OO} \\
\gamma^{UU}_{EE}-\gamma^{UU}_{OO} & \gamma^{UU}_{EU}-\gamma^{UU}_{OO} & \gamma^{UU}_{EO}-\gamma^{UU}_{OO} & \gamma^{UU}_{UE}-\gamma^{UU}_{OO} & \gamma^{UU}_{UU}-\gamma^{UU}_{OO} & \gamma^{UU}_{UO}-\gamma^{UU}_{OO} & \gamma^{UU}_{OE}-\gamma^{UU}_{OO} & \gamma^{UU}_{OU}-\gamma^{UU}_{OO} \\
\gamma^{UO}_{EE}-\gamma^{UO}_{OO} & \gamma^{UO}_{EU}-\gamma^{UO}_{OO} & \gamma^{UO}_{EO}-\gamma^{UO}_{OO} & \gamma^{UO}_{UE}-\gamma^{UO}_{OO} & \gamma^{UO}_{UU}-\gamma^{UO}_{OO} & \gamma^{UO}_{UO}-\gamma^{UO}_{OO} & \gamma^{UO}_{OE}-\gamma^{UO}_{OO} & \gamma^{UO}_{OU}-\gamma^{UO}_{OO} \\
\gamma^{OE}_{EE}-\gamma^{OE}_{OO} & \gamma^{OE}_{EU}-\gamma^{OE}_{OO} & \gamma^{OE}_{EO}-\gamma^{OE}_{OO} & \gamma^{OE}_{UE}-\gamma^{OE}_{OO} & \gamma^{OE}_{UU}-\gamma^{OE}_{OO} & \gamma^{OE}_{UO}-\gamma^{OE}_{OO} & \gamma^{OE}_{OE}-\gamma^{OE}_{OO} & \gamma^{OE}_{OU}-\gamma^{OE}_{OO} \\
\gamma^{OU}_{EE}-\gamma^{OU}_{OO} & \gamma^{OU}_{EU}-\gamma^{OU}_{OO} & \gamma^{OU}_{EO}-\gamma^{OU}_{OO} & \gamma^{OU}_{UE}-\gamma^{OU}_{OO} & \gamma^{OU}_{UU}-\gamma^{OU}_{OO} & \gamma^{OU}_{UO}-\gamma^{OU}_{OO} & \gamma^{OU}_{OE}-\gamma^{OU}_{OO} & \gamma^{OU}_{OU}-\gamma^{OU}_{OO}
\end{pmatrix}_t}_{\Gamma_t}
$$

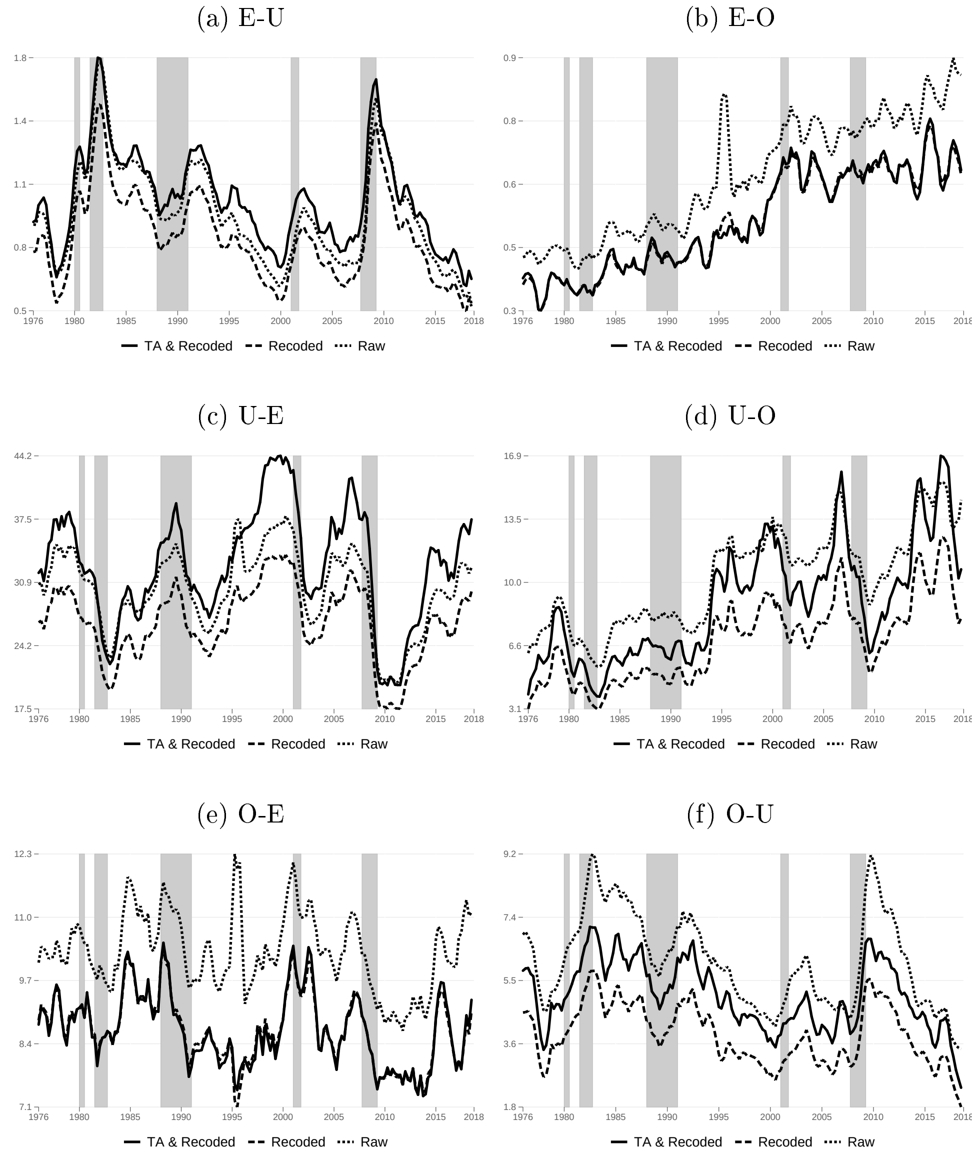
$$
\times \underbrace{\begin{pmatrix} EE \\ EU \\ EO \\ UE \\ UU \\ UO \\ OE \\ OU \end{pmatrix}_{t-1}}_{s_{t-1}} + \underbrace{\begin{pmatrix} \gamma^{EE}_{OO} \\ \gamma^{EU}_{OO} \\ \gamma^{EO}_{OO} \\ \gamma^{UE}_{OO} \\ \gamma^{UU}_{OO} \\ \gamma^{UO}_{OO} \\ \gamma^{OE}_{OO} \\ \gamma^{OU}_{OO} \end{pmatrix}_t}_{g_t}
$$

The analogous continuous time equation to this Markov chain is $\dot{s}_t = \Pi_t s_t + q_t$, where q_t is continuous-time version of g_t. From the discrete-time version, $s_t = \Gamma_t s_{t-1} + g_t$ we find the steady state of the discrete Markov chain by $\overline{s}_t = (I - \Gamma_t)^{-1} g_t$. The steady state of the continuous time analogue is: $0 = \Pi_t s_t + q_t \Rightarrow \overline{s}_t = -\Pi^{-1} q_t$. Thus, steady state satisfies $\overline{s_t} = (I - \Gamma_t)^{-1} g_t = -\Pi^{-1} q_t$.

Now, let's calculate deviations from the steady state $\psi = (s_t - \overline{s_t})$. We can apply this transformation to the discrete time equation and get $s_t - \overline{s_t} = \Gamma_t(s_{t-1} - \overline{s}_{t-1})$, which is the same as $\psi_t = \Gamma_t \psi_{t-1}$. Analogously for continuous time we get $\dot{\psi}_t = \Pi_t \psi_t$.

The latter differential equation has a solution $\psi_t = \Omega_t \Lambda_t \Omega_t^{-1} \psi_{t-1}$, where Ω_t is a matrix of eigenvectors of the matrix Π_t, and Λ_t is a matrix, whose diagonal elements are equal to the exponent of eigenvalues of the matrix Π_t. It follows that $\Gamma_t = \Omega_t \Lambda_t \Omega_t^{-1}$. The latter implies that the eigenvectors of the matrix Γ_t are the same as those of the Π_t, and that the eigenvalues of Γ_t are equal to the exponentiated eigenvalues of Π_t. Hence, given an estimate of Γ_t that we observe from the data, we can find out matrix of continuous transitions Π_t through the eigenvalue decomposition of the matrix Γ_t.

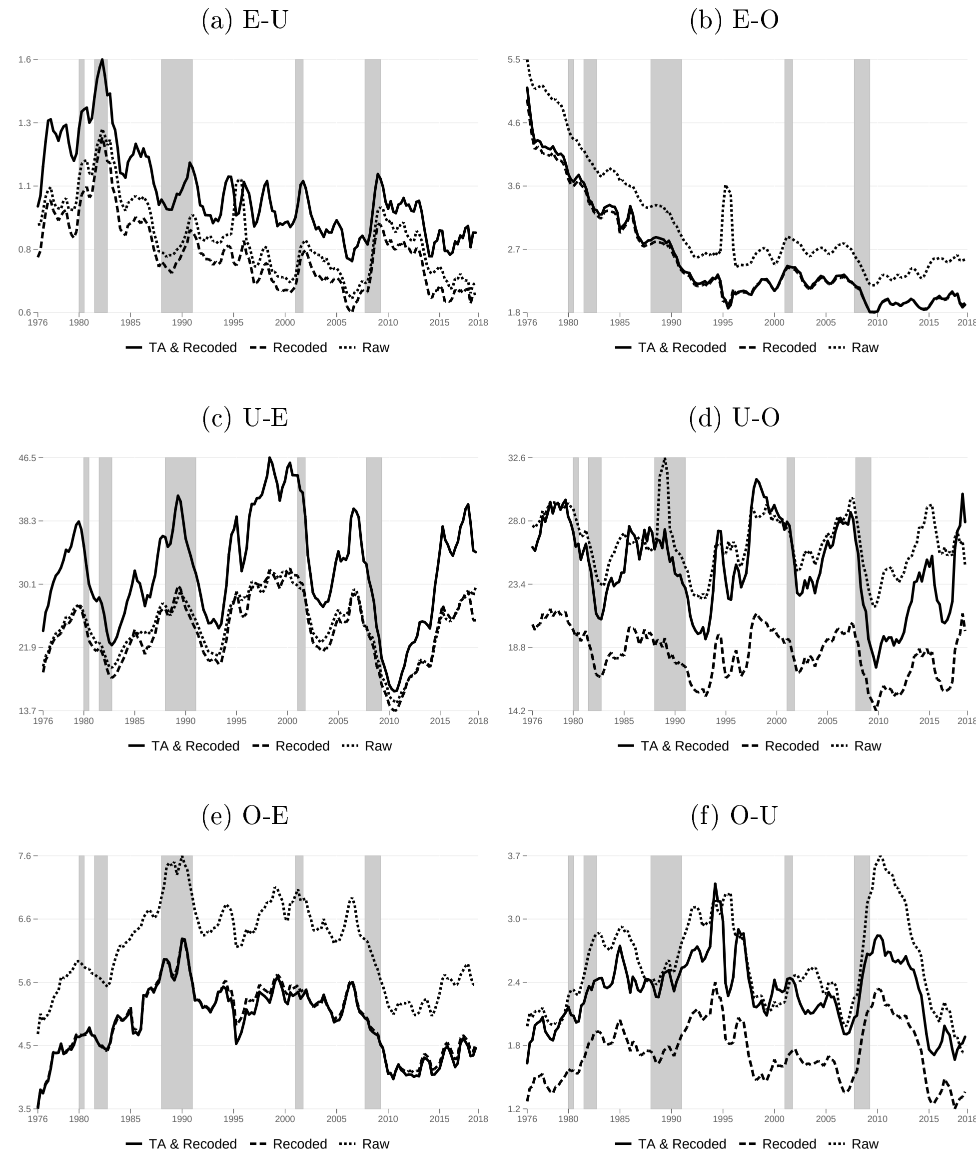
Figure A.1: Unconditional Labor Market Transitions of Married Men



Note: CPS 1976:Q1 to 2018:Q3. Married men aged 25-54. Dotted lines represent raw data transitions, dashed lines represent transitions corrected for the classification error, solid lines represent transitions adjusted for classification error and time aggregation bias. Quarterly average of monthly data. Seasonally adjusted using a 12-month moving average. Grey areas represent NBER recession periods.

In Figure A.1 and Figure A.2 we present estimates of labor market flows that are adjusted for the time aggregation (after correction for the classification errors), together with the raw flows and flows that are adjusted for the classification errors. The effect of time-aggregation bias is minimal on transitions between employment and out of labor force states. On the other hand, for all other transitions to and from unemployment, correcting for the time aggregation bias results in higher levels of transitions.

Figure A.2: Unconditional Labor Market Transitions of Married Women



NOTE: CPS 1976:Q1 to 2018:Q3. Married women aged 25-54. Dotted lines represent raw data transitions, dashed lines represent transitions corrected for the classification error, solid lines represent transitions adjusted for classification error and time aggregation bias. Quarterly average of monthly data. Seasonally adjusted using a 12-month moving average. Grey areas represent NBER recession periods.

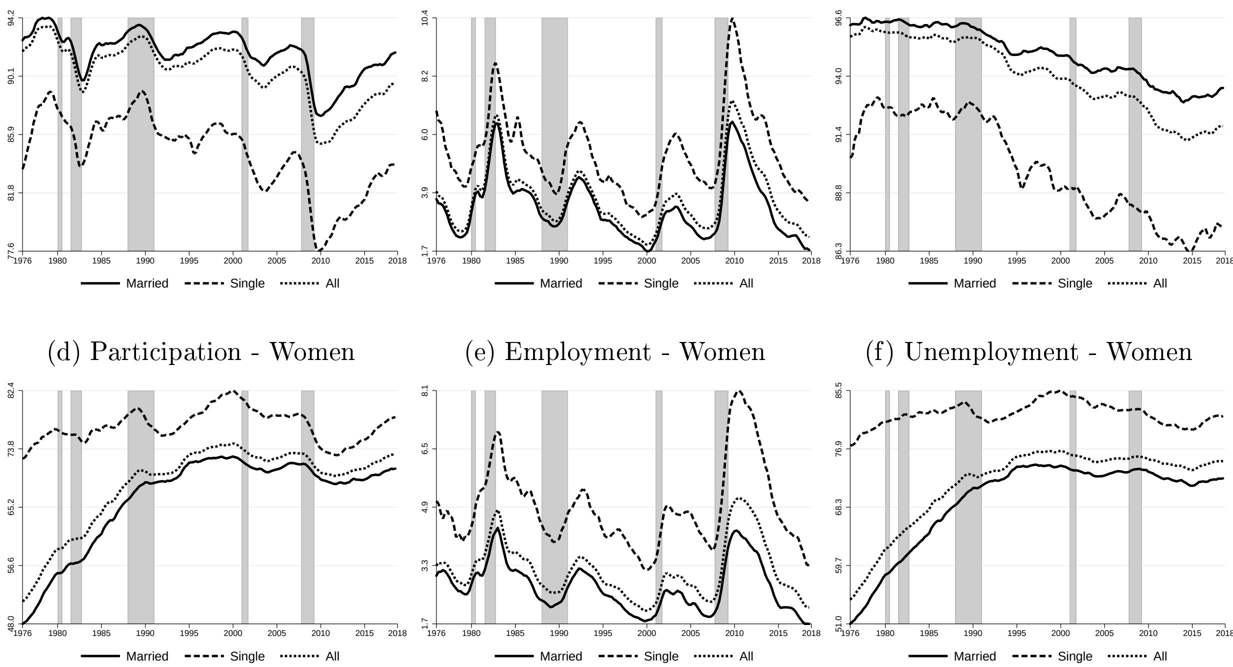
A.2 Labor Market Stocks of Single, Married and All Individuals

In this subsection we show the unemployment, (U/P), employment, (E/L) and participation (P/L) rates for married, single, and all individuals, where $P = E + U$ and total population is $L = P + O$.

Figure A.3: Labor Market Stocks of Single, Married and All Individuals

(a) Participation - Men (b) Employment - Men (c) Unemployment - Men

(d) Participation - Women (e) Employment - Women (f) Unemployment - Women



NOTE: CPS 1976:Q1 to 2018:Q3. All individuals aged 25-54. Quarterly averages of monthly data. Seasonally adjusted using a 12-month moving average. Adjusted for classification errors. The solid line represents married individuals, dashed line - all population. Grey areas represent NBER recession periods.

A.3 Joint Labor Market Transitions of Married Couples

In this appendix we document joint labor market transitions of spouses across joint labor market outcomes. Each joint labor market state is comprised of two letters, first corresponds to husband, second corresponds to wife. E is employed, U - uenmployed, O - out-of-the labor force. Thus, EU stands for an employed husband and an unemployed wife. Each number corresponds to a probability of a couple of transiting from the state on the lines to the state in columns.

Table A.2: Joint Average Labor Market Transitions of Married Couples

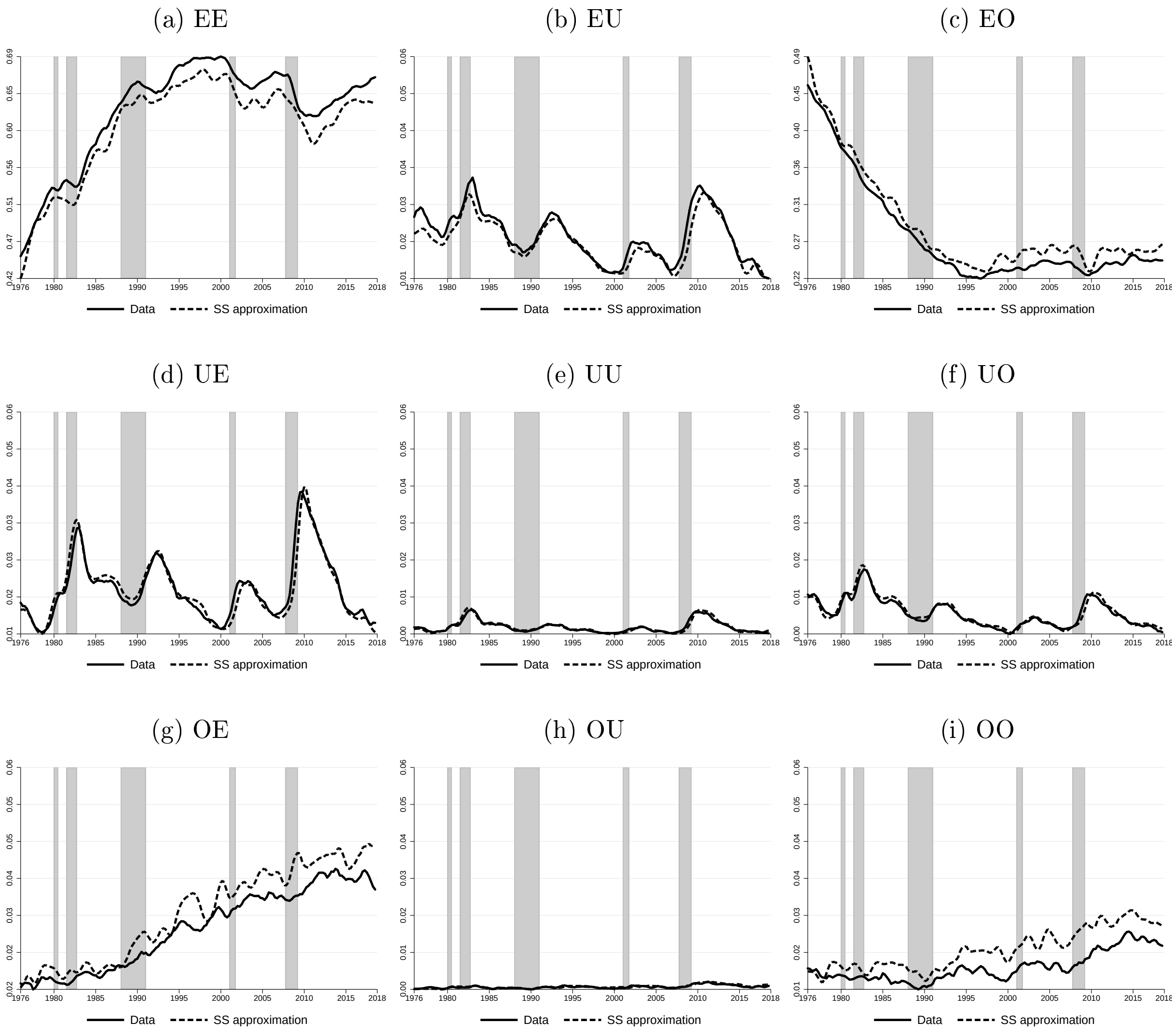
	EE	EU	EO	UE	UU	UO	OE	OU	OO
EE	95.00	0.96	2.52	0.95	0.04	0.02	0.43	0.01	0.06
EU	32.43	38.42	24.86	0.47	2.38	0.39	0.25	0.55	0.24
EO	4.89	2.17	91.14	0.04	0.04	1.07	0.06	0.01	0.57
UE	31.38	0.54	0.53	54.62	2.18	1.76	8.66	0.09	0.23
UU	6.52	21.26	3.01	18.20	26.11	15.67	1.52	4.82	2.89
UO	1.54	1.05	34.21	3.53	7.03	42.05	0.49	0.37	9.73
OE	8.34	0.12	0.46	5.49	0.13	0.10	81.75	1.37	2.24
OU	2.94	7.27	2.22	1.84	6.97	1.97	23.55	29.96	23.29
OO	1.74	0.31	6.94	0.19	0.38	3.86	2.71	1.93	81.94

NOTE: CPS 1976:Q1 to 2018:Q3. All individuals aged 25-54. Percentage of people transiting from the labor state in the row to each of the labor states in columns. In each stock XY, X refers to the male and Y to the female. X and Y can stand for: E - employed, U - unemployed, O - out of the labor force. Adjusted for classification errors, seasonality (12-months moving average) and time aggregation bias.

Appendix B: Added Worker Effect

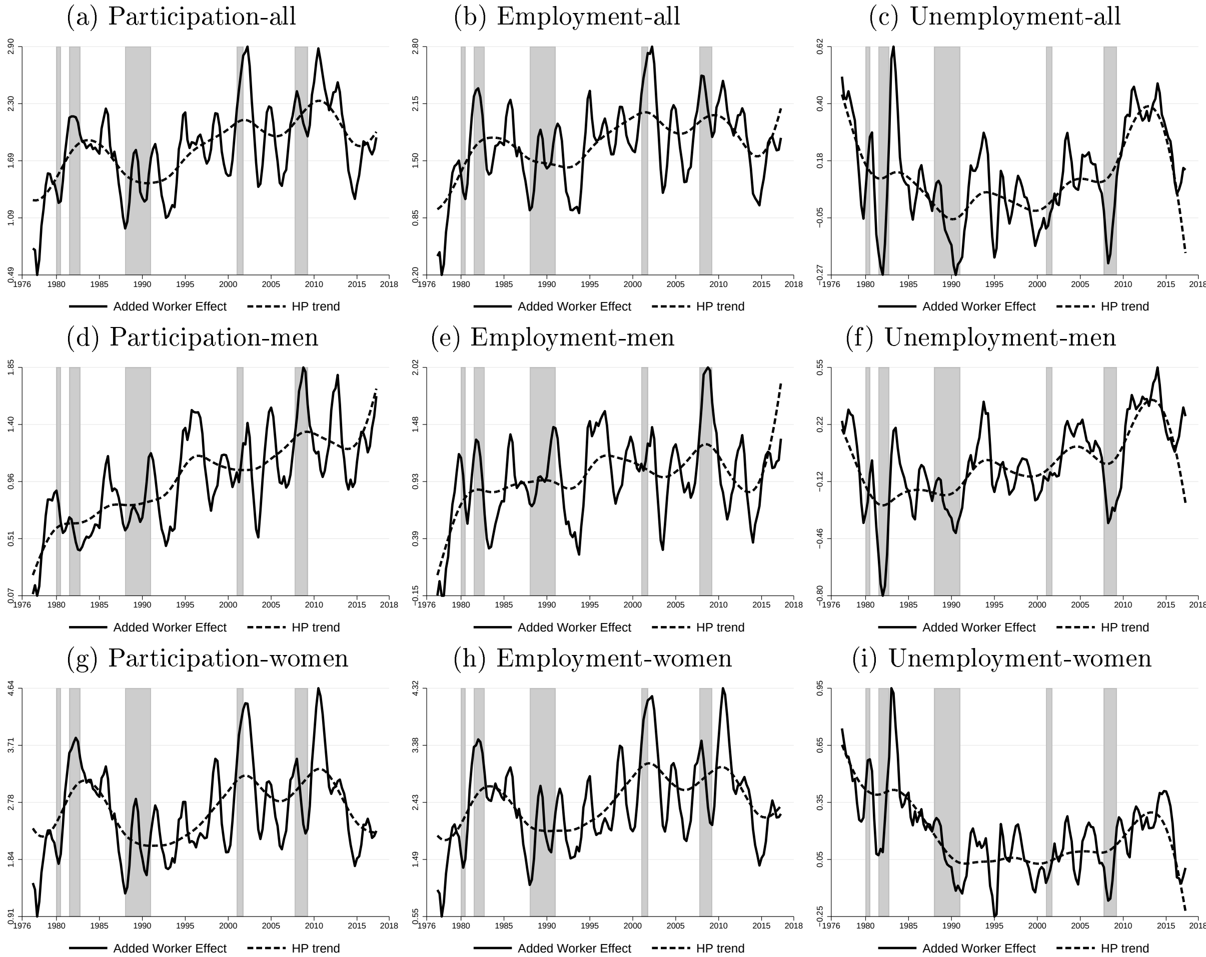
In Figure B.1 we present how well themethodology of Shimer (2012) allows us to approximate the observed data. In Figure B.2 we show the evolution of the added worker effect, calculated as a difference between the original data series and the artificial series that we calculate using the aforementioned methodology. In Table B.1 we present the added worker effect in recessions and expansions.

Figure B.1: Data and Steady State Approximation



Note: CPS 1976:Q1 to 2018:Q3. All individuals aged 25-54. Adjusted for classification errors. Seasonally adjusted using a 12-month moving average. Quarterly average of monthly data. Each joint stock is denoted by two letter XY, where X refers to the male and Y to the female. X and Y can stand for: E - employed, U - unemployed, O - out of the labor force. Solid lines represent joint labor market stocks in the data, dashed lines correspond to steady state approximation of these stocks, implied by the continuous time joint transitions matrix. Grey areas represent NBER recessions.

Figure B.2: Added Worker Effect



Note: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. Monthly series smoothed using a 12-month moving average, adjusted for classification errors, corrected for time aggregation bias, and presented averaged across quarters. Solid line corresponds to the size of the added worker effect, that we get by substracting from the data counterfactual stocks with no added-worker effect. Dashed line corresponds to the trend of the data after applying HP-filter with the smoothing factor 1600. Grey areas represent NBER recession periods.

Table B.1: Role of Added Worker Effect, Expansions and Recessions

Expansions

	1977Q2 1979Q4	1980Q4 1981Q2	1983Q1 1987Q4	1991Q2 2000Q4	2002Q1 2007Q3	2009Q3 2017Q3	Total
All							
Participation Rate	1.12	1.74	1.80	1.73	1.97	2.08	1.82
Employment Rate	0.90	1.64	1.64	1.66	1.81	1.75	1.64
Unemployment Rate	0.29	0.08	0.16	0.02	0.13	0.30	0.16
Males							
Participation Rate	0.44	0.61	0.76	1.03	1.06	1.24	0.98
Employment Rate	0.36	0.74	0.85	1.03	0.92	0.90	0.88
Unemployment Rate	0.08	-0.16	-0.13	-0.03	0.11	0.32	0.07
Females							
Participation Rate	1.80	2.88	2.84	2.43	2.89	2.92	2.65
Employment Rate	1.45	2.55	2.42	2.29	2.69	2.60	2.39
Unemployment Rate	0.50	0.32	0.44	0.08	0.15	0.27	0.24

Recessions

	1980Q1 1980Q3	1981Q3 1982Q4	1988Q1 1991Q1	2001Q1 2001Q4	2007Q4 2009Q2	Total
All						
Participation Rate	1.30	2.12	1.44	2.53	2.19	1.84
Employment Rate	1.18	2.14	1.49	2.50	2.18	1.85
Unemployment Rate	0.17	-0.09	-0.09	-0.05	-0.08	-0.06
Males						
Participation Rate	0.75	0.50	0.81	1.06	1.59	0.94
Employment Rate	0.94	0.98	1.05	1.15	1.70	1.18
Unemployment Rate	-0.22	-0.52	-0.27	-0.12	-0.19	-0.28
Females						
Participation Rate	1.84	3.73	2.06	3.99	2.79	2.73
Employment Rate	1.43	3.30	1.93	3.86	2.66	2.52
Unemployment Rate	0.56	0.35	0.09	0.02	0.03	0.16

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. Numbers in the table represent differences between the means of the data and counterfactual experiment calculations (in which added worker effect is shut down) in percentage points, for different time periods, recessions and expansions. Dates of recessions are taken from NBER website.

Appendix C: Added Worker Effect due to Job Loss of Partners

The existing measures of the AWE that can be found in the literature focus exclusively on the entry of the women into the labor force that is associated to a husband's job loss. They do not take into account a more prolonged effect of women entering labor force in response to their husband staying unemployed. We use our methodology to calculate this, more common and conservative, measure of AWE effect. We do the following modifications to the transition matrices, for $g = \{M, W\}$:

$$\pi^{g^{noAWE}}_{OE|EU} = \pi^{g^{noAWE}}_{OU|EU} = 0,$$

and

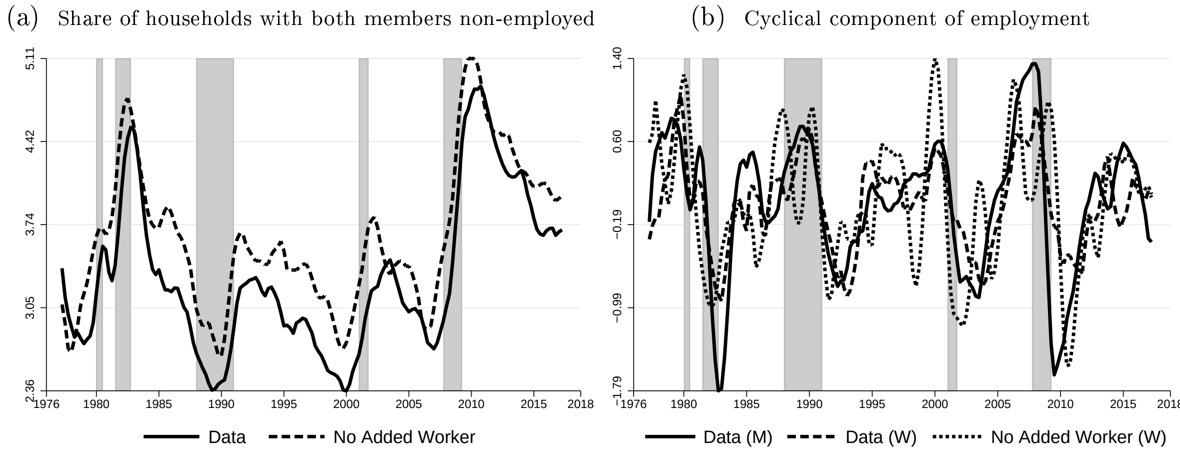
$$\pi^{g^{noAWE}}_{OO|EU} = \pi^{g}_{OO|EU} + \pi^{g}_{OE|EU} + \pi^{g}_{OU|EU}$$

Table C.1: Added Worker Effect, Individuals
(only considering job loss by partners)

	1977-2017	1980-1990	1990-2000	2000-2010	2010-2017
All					
Participation Rate	1.28	1.03	1.19	1.62	1.48
Employment Rate	1.21	1.04	1.20	1.56	1.23
Unemployment Rate	0.05	-0.03	-0.05	0.02	0.22
Males					
Participation Rate	0.76	0.51	0.78	0.97	0.95
Employment Rate	0.76	0.71	0.83	0.94	0.66
Unemployment Rate	-0.02	-0.23	-0.08	0.00	0.28
Females					
Participation Rate	1.78	1.53	1.58	2.28	2.00
Employment Rate	1.66	1.37	1.55	2.20	1.82
Unemployment Rate	0.09	0.15	-0.02	0.01	0.12

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent differences between the means of the data and the counterfactual experiment calculations in percentage points, for different time periods. In the upper panel we shut down all transitions mentioned below (the added worker effect for males and females). In the middle panel we shut down transitions corresponding to males' AWE: OE to EU, OE to UU. In the lower panel we shut down the joint transitions, corresponding to females' AWE: EO to UE, EO to UU.

Figure C.1: Added Worker Effect, Households
(only considering job loss by partners)



NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. In the panel C.1a, the solid line represents the share of households with two non-employed members. The dashed line represent the results of counterfactual experiments in which we shut down the AWE due to partner's job loss in the economy. In the panel C.1b, the solid line represents cyclical component of men's employment, the dashed line represents the cyclical component of women's employment, and the dotted line represents the cyclical component of the counterfactual women's employment rate in the economy with the added worker effect shut down. Monthly series smoothed using a 12-month moving average, adjusted for classification errors, corrected for time aggregation bias, HP-filtered with a smoothing parameter 1600 and presented averaged across quarters. Grey areas represent NBER recession periods.

This specification results in lower values of the AWE. The AWE for women's employment in our main specification, for example, was 2.42 p.p. in 1977-2017. It is 1.66 p.p. for this alternative specification.

Table C.2: Added Worker Effect, Volatility and Skewness
(only considering job loss by partners)

	Volatility	Cyclical Volatility	SD/SD_{GDP}	Skewness in levels	Skewness in growth rates
			Men		
Participation	0.11	0.03	0.08	-0.12	0.18
				[0.516]	[0.338]
Employment	0.64	0.55	0.47	-0.61	-1.21
				[0.002]	[0.000]
Unemployment	0.62	0.54	0.46	0.81	1.33
				[0.000]	[0.000]
			Women		
Participation	0.24	0.04	0.18	-0.07	0.40
				[0.717]	[0.036]
Employment	0.43	0.29	0.32	-0.09	0.40
				[0.634]	[0.038]
Unemployment	0.45	0.38	0.33	0.49	0.64
				[0.012]	[0.001]
			Without the added-worker effect		
			Women		
Participation	0.52	0.01	0.38	0.35	-0.29
				[0.069]	[0.126]
Employment	0.63	0.26	0.47	-0.16	-0.40
				[0.391]	[0.038]
Unemployment	0.46	0.37	0.34	0.38	0.60
				[0.045]	[0.003]

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent standard deviations of the cyclical component, standard deviation of the predicted values of labor market states from the regression of cyclical component of labor state on cyclical component of log-GDP, ratios of standard deviations of the cyclical component of labor market state and cyclical component of GDP, skewness of cyclical component after HP-filtering ("in levels"), and skewness of the growth rates in the data and in the counterfactual steady state of the economy without an added-worker effect. P-values in brackets.

Appendix D: Added Worker Effect – Alternative Specification

To calculate the AWE in Section 4, we replace the AWE transitions with zero and assume that the wife (or husband) stays in her (or his) state. For example, $\pi_{EO,UE}$ is set to zero, and this probability is added to $\pi_{EO,UO}$. An alternative would be to replace $\pi_{EO,UE}$ not with zero but with $\pi_{EO,EE}$. This alternative assumes that some women move from O to E even if their husbands stay employed and considers transition beyond that as part of the AWE. Hence for $g = \{M, W\}$, we set

$$\pi^{g^{noAWE}}_{OE|EU} = \pi^{g}_{OE|EE},\ \pi^{g^{noAWE}}_{OU|EU} = \pi^{g}_{OU|EE},\ \pi^{g^{noAWE}}_{OE|UU} = \pi^{g}_{OE|EE} \text{ and } \pi^{g^{noAWE}}_{OU|UU} = \pi^{g}_{OU|EE}.$$

If an AWE transition is smaller than the alternative transition (e.g. $\pi^{g}_{OE|EU} \leq \pi^{g}_{OE|EE}$), we keep the original value intact.

To make sure the alternative matrix is a transition matrix, i.e. all the rows should sum up to one, we move the difference between the original and the alternative value to the transition in which husband/wife looses the job or stays unemployed, but his/her partner stays out of the labor force instead of entering the labor market, i.e., we set

$$\pi^{g^{noAWE}}_{OO|EU} = \pi^{g}_{OO|EU} + (\pi^{g}_{OE|EU} - \pi^{g}_{OE|EE}) + (\pi^{g}_{OU|EU} - \pi^{g}_{OU|EE}),$$

and

$$\pi^{g^{noAWE}}_{OO|UU} = \pi^{g}_{OO|UU} + (\pi^{g}_{OE|UU} - \pi^{g}_{OE|EE}) + (\pi^{g}_{OU|UU} - \pi^{g}_{OU|EE})$$

This specification gives us smaller numbers for AWE. However, as Table D.1 and Figure D.1 show, qualitatively the results are very similar to our main specification.

Table D.1: Added Worker Effect, Individuals
(Alternative Specification)

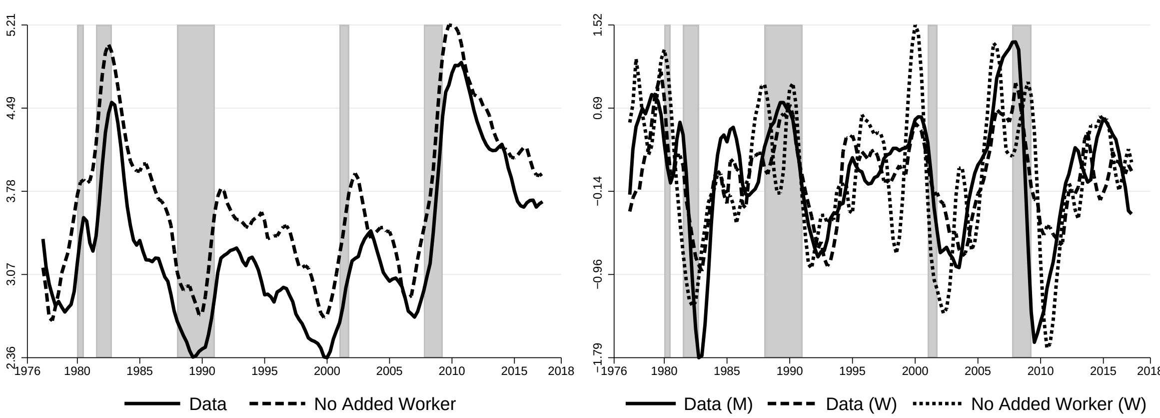
	1977-2017	1980-1990	1990-2000	2000-2010	2010-2017
All					
Participation Rate	1.43	1.32	1.31	1.73	1.58
Employment Rate	1.34	1.30	1.30	1.64	1.31
Unemployment Rate	0.06	-0.01	-0.04	0.04	0.24
Males					
Participation Rate	0.73	0.48	0.74	0.94	0.92
Employment Rate	0.72	0.68	0.79	0.90	0.63
Unemployment Rate	-0.01	-0.23	-0.07	0.01	0.28
Females					
Participation Rate	2.12	2.13	1.84	2.54	2.24
Employment Rate	1.96	1.91	1.79	2.42	2.03
Unemployment Rate	0.12	0.20	-0.01	0.04	0.16

Note: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent differences between the means of the data and the counterfactual experiment calculations (in which the added worker effect is shut down) in percentage points, for different time periods. In the upper panel we shut down all transitions mentioned below (the added worker effect for males and females). In the middle panel we shut down transitions corresponding to males' added worker effect: OE to EU, OU to EU, OE to UU, and OU to UU. In the lower panel we shut down the joint transitions, corresponding to females' added worker effect: EO to UE, UO to UE, EO to UU, and UO to UU.

Figure D.1: Added Worker Effect, Households
(Alternative Specification)

(a) Share of households with both members non-employed

(b) Cyclical component of employment



Note: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. In the panel D.1a, the solid line represents the share of households with two non-employed members. The dashed line represent the results of counterfactual experiments in which we shut down the "classic" added-worker effect in the economy. In the panel D.1b, the solid line represents cyclical component of men's employment, the dashed line represents the cyclical component of women's employment, and the dotted line represents the cyclical component of the counterfactual women's employment rate in the economy with the added worker effect shut down. Monthly series smoothed using a 12-month moving average, adjusted for classification errors, corrected for time aggregation bias, HP-filtered with a smoothing parameter 1600 and presented averaged across quarters. Grey areas represent NBER recession periods.

Table D.2: AWE, Volatility and Skewness
(Alternative Specification)

	Volatility	Cyclical Volatility	SD/SD_{GDP}	Skewness in levels	Skewness in growth rates
			Men		
Participation	0.11	0.03	0.07	-0.12	0.18
				[0.516]	[0.338]
Employment	0.64	0.48	0.41	-0.61	-1.21
				[0.002]	[0.000]
Unemployment	0.62	0.48	0.40	0.81	1.33
				[0.000]	[0.000]
			Women		
Participation	0.24	0.02	0.16	-0.07	0.40
				[0.717]	[0.036]
Employment	0.43	0.25	0.27	-0.09	0.40
				[0.634]	[0.038]
Unemployment	0.45	0.34	0.29	0.49	0.64
				[0.012]	[0.001]
			Without the added-worker effect		
			Women		
Participation	0.55	0.11	0.35	0.21	-0.36
				[0.252]	[0.062]
Employment	0.69	0.32	0.44	-0.24	-0.40
				[0.192]	[0.038]
Unemployment	0.44	0.33	0.28	0.33	0.61
				[0.085]	[0.002]

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent standard deviations of the cyclical component, standard deviation of the predicted values of labor market states from the regression of cyclical component of labor state on cyclical component of log-GDP, ratios of standard deviations of the cyclical component of labor market state and cyclical component of GDP, skewness of cyclical component after HP-filtering ("in levels"), and skewness of the growth rates in the data and in the counterfactual steady state of the economy without an added-worker effect. P-values in brackets.

Appendix E: Role of Changing Demographics

E.1 Does the Demographic Composition Matter for Labor Market Outcomes?

In this section of the Appendix, we explore how changes in the US population's demographic composition between 1976 and 2018 affect our results. Between 1976 and 2018, the US population changed significantly along several dimensions. We focus on i) age, ii) race (share of individuals of whites and non-whites), iii) geography (share of individuals living in different US states), iv) education (share of individuals with and without a college degree), and v) presence of children (share of individuals with and without children). To capture the effect of these demographic changes, we construct artificial populations where we keep the demographic composition at its 1976-79 level.

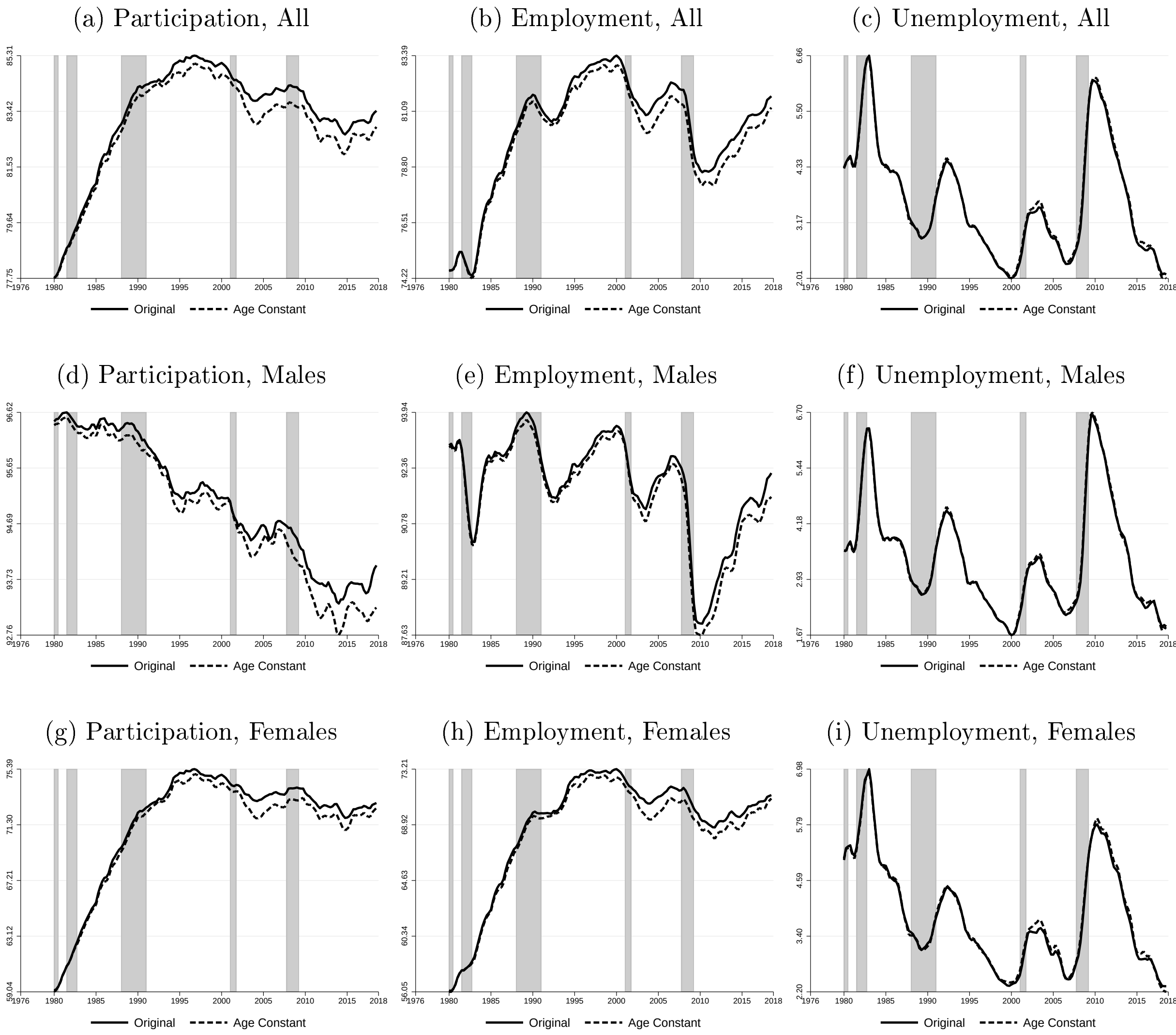
To construct these artificial samples, we employ a simple matching algorithm.[16] For each month in the sample, we create bins for observable characteristics of households (age of spouses, race, geography, education of spouses and the dummy for having children). There are in total around 700 bins for age (age of husband 25-54 and age of wife 25-54 in different combinations), 2 for the race (white vs. non-white), 51 for geography (the number of US states), 4 for education (college vs. non-college for husbands and wives) and 2 for the dummy of having children (0 vs. 1). We then compare the number of observations in these bins with the number of observations in the same bins in the base period (1976-1979).[17] If there hadn't been any change in the composition of the US population along these dimensions, the number of observations in each bin would be constant. Suppose there are more observations in a particular bin in the base-period than in the current one. Then, we perform a bootstrap-like replacement of observations in the current period with observations in the base period at random to equate the number of observations. In contrast, if there are more observations in

[16]See Angrist (1998) for details on matching.

[17]Due to change in CPS methodology of recording the number of children in the household in 1982, we use 1982-1985 as base years for the sample on children composition.

the current period than in the base period for a bin, we erase observations from the current period at random. We also record the transitions of households in these bins between two consecutive months.

Figure E.1: Individual Stocks, with 1976-1979 Age Structure



(a) Participation, All

(b) Employment, All

(c) Unemployment, All

(d) Participation, Males

(e) Employment, Males

(f) Unemployment, Males

(g) Participation, Females

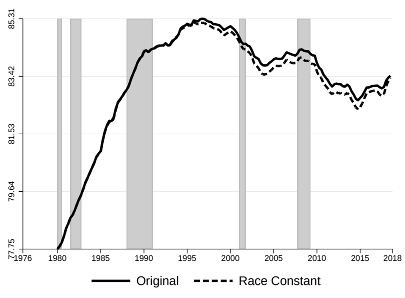
(h) Employment, Females

(i) Unemployment, Females

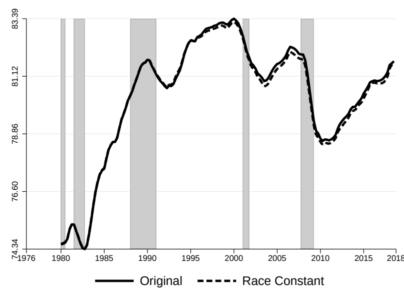
Figures E.1 - E.5 show the individual labor market outcomes (P, E, and U) for the original and artificial data. Changes in the population's composition in age, race, geography, and presence of children do not affect these labor market outcomes. On the other hand, changes in the educational attainment do. If the US population's educational attainment remained constant, i.e., there was no increase in the fraction of the US population with a college degree, participation and employment would be much lower. This is true for both males and females. Given the importance of education, in Section E.2 we document how the US population changes along educational attainment affect our results.

Figure E.2: Individual Stocks, with 1976-1979 Race Composition

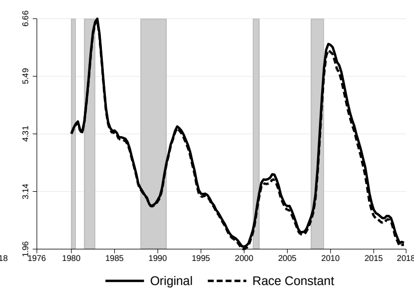
(a) Participation, All



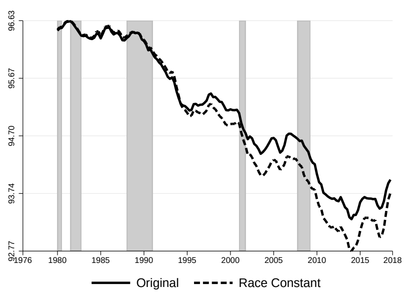
(b) Employment, All



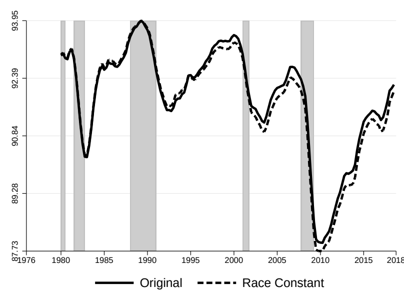
(c) Unemployment, All



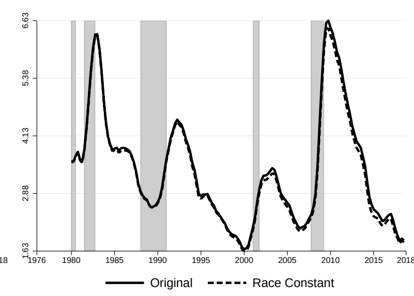
(d) Participation, Males



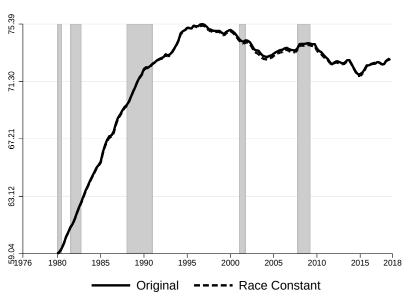
(e) Employment, Males



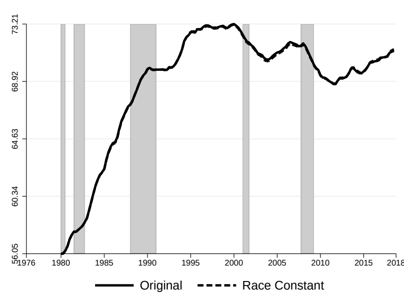
(f) Unemployment, Males



(g) Participation, Females



(h) Employment, Females



(i) Unemployment, Females

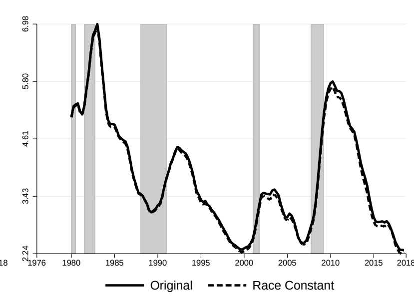


Figure E.3: Individual Stocks, with 1976-1979 Distribution of the US Population across States

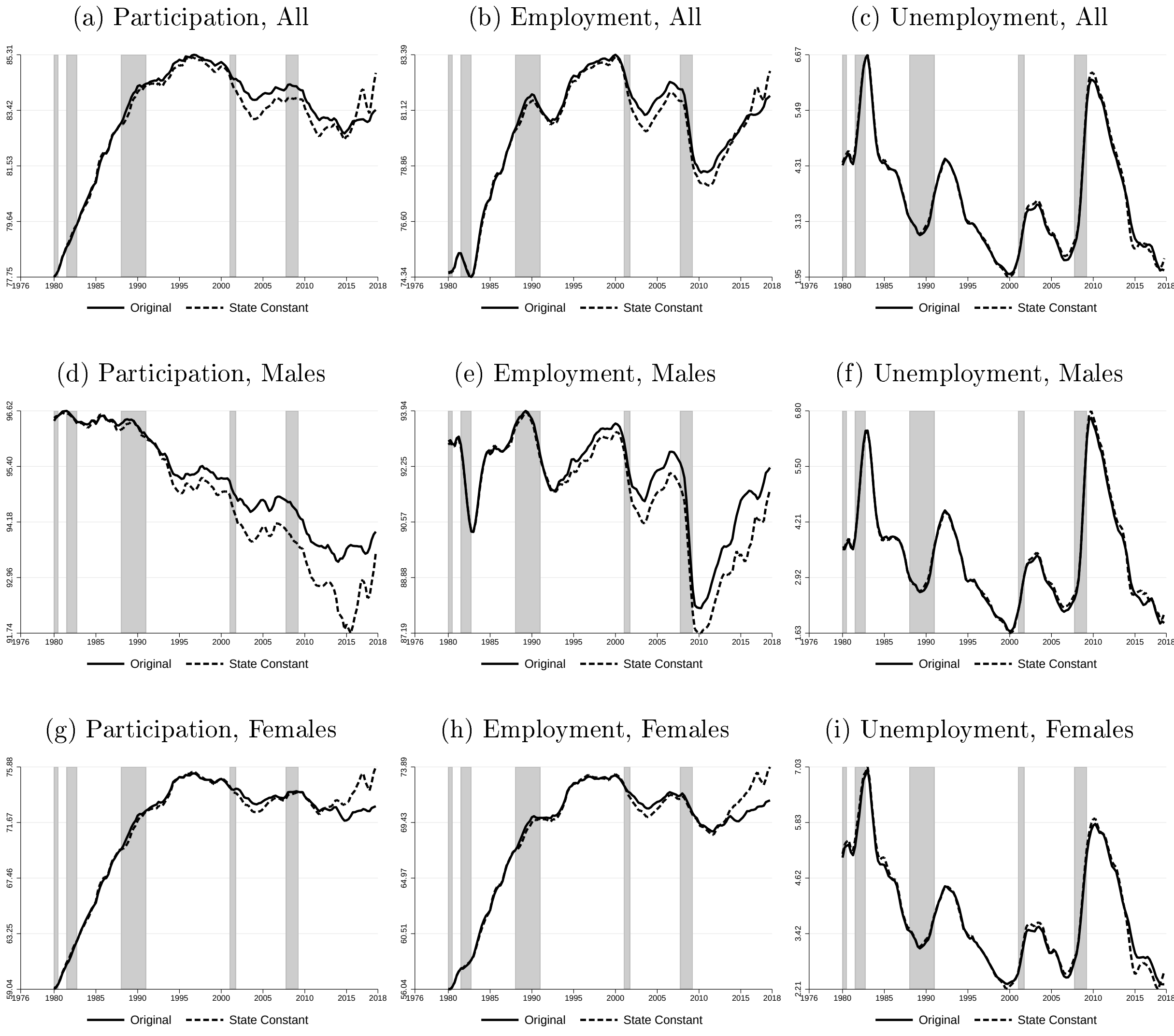


Figure E.4: Individual Stocks, with 1976-1979 College Attainment

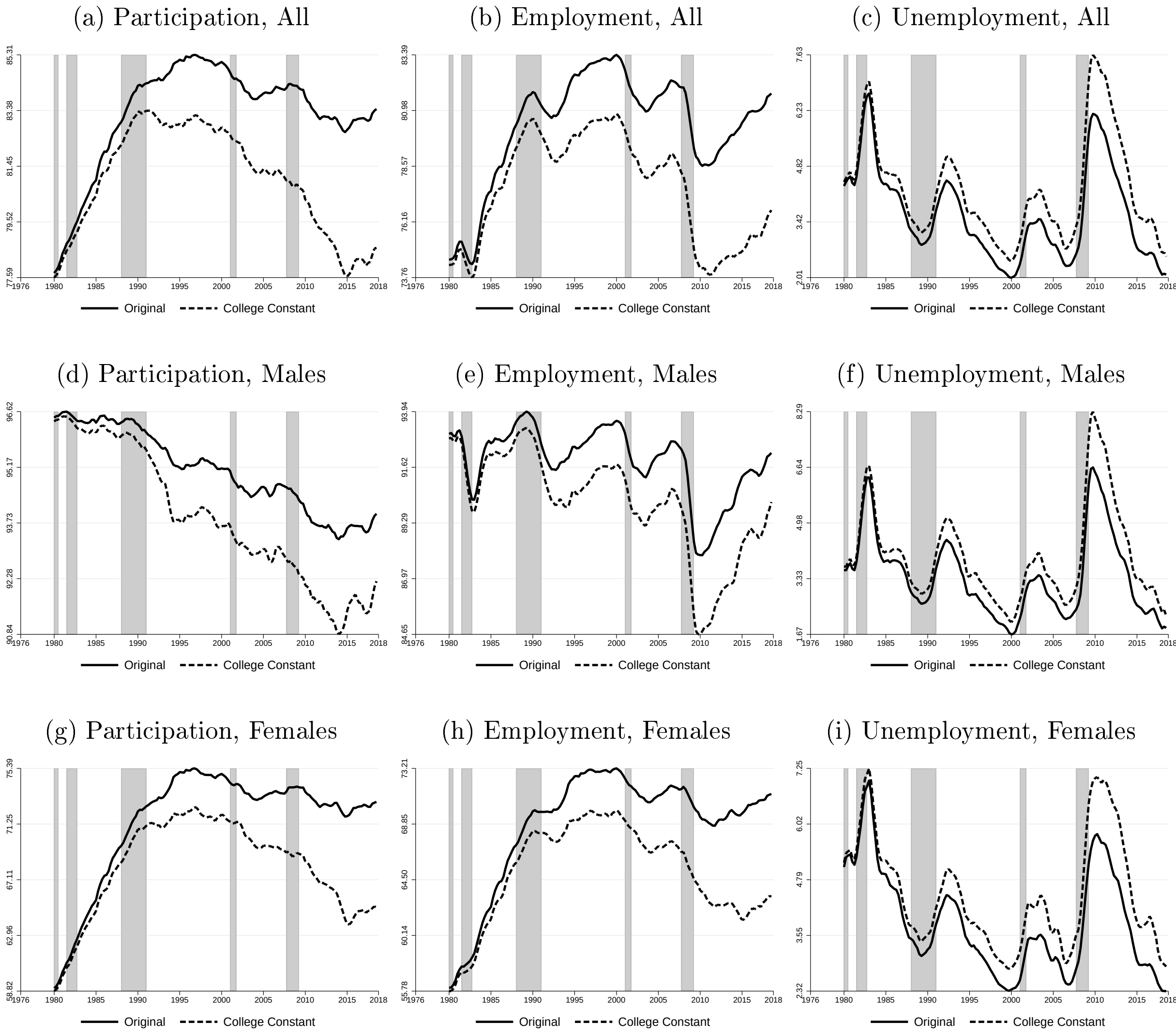
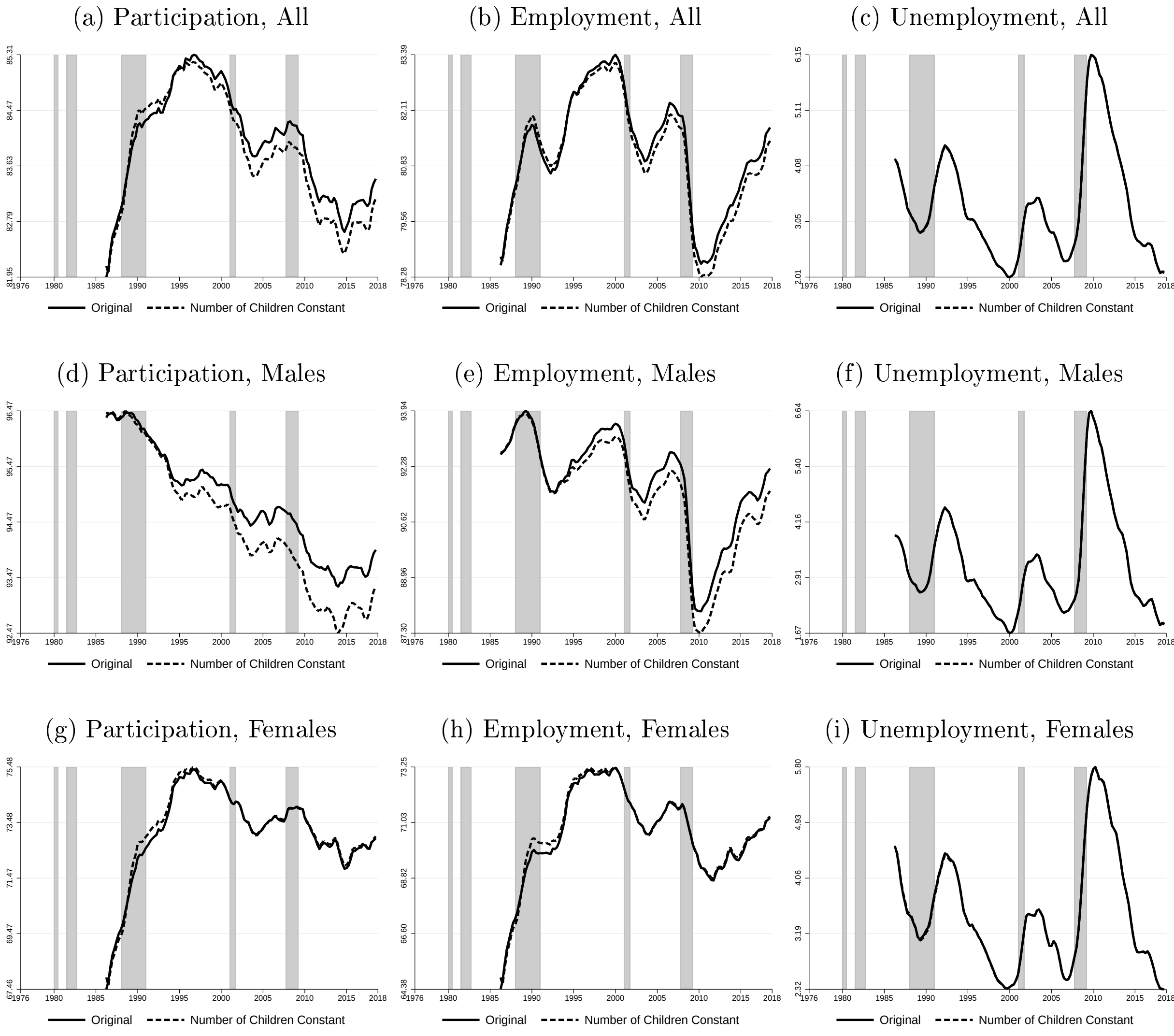


Figure E.5: Individual Stocks, with 1982-1985 Distribution of Presence of Children



E.2 The Added Worker Effect Keeping Educational Composition Constant

In this section we keep the educational composition of households constant and recalculate the results presented in the main text in Tables 2 and 3 and Figure 1.

Table E.1: Added Worker Effect, Individuals
(educational composition constant)

	1977-2017	1980-1990	1990-2000	2000-2010	2010-2017
All					
Participation Rate	2.32	1.97	2.03	2.66	2.79
Employment Rate	2.16	1.91	1.98	2.46	2.44
Unemployment Rate	0.08	0.02	-0.02	0.11	0.25
Males					
Participation Rate	1.25	0.84	1.22	1.41	1.69
Employment Rate	1.20	1.03	1.22	1.30	1.32
Unemployment Rate	0.00	-0.24	-0.05	0.05	0.32
Females					
Participation Rate	3.36	3.04	2.73	3.96	3.94
Employment Rate	3.13	2.75	2.64	3.72	3.66
Unemployment Rate	0.12	0.23	-0.01	0.09	0.10

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent differences between the means of the data and the counterfactual experiment calculations (in which the added worker effect is shut down) in percentage points, for different time periods. In the upper panel we shut down all transitions mentioned below (the added worker effect for males and females). In the middle panel we shut down transitions corresponding to males' added worker effect: OE to EU, OU to EU, OE to UU, and OU to UU. In the lower panel we shut down the joint transitions, corresponding to females' added worker effect: EO to UE, UO to UE, EO to UU, and UO to UU.

Figure E.6: Added Worker Effect, Households
(educational composition constant)

(a) Share of households with both members non-employed (b) Cyclical component of employment

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. In the panel E.6a, the solid line represents the share of households with two non-employed members. The dashed line represent the results of counterfactual experiments in which we shut down added-worker effect in the economy. In the panel E.6b, the solid line represents cyclical component of men's employment, the dashed line represents the cyclical component of women's employment, and the dotted line represents the cyclical component of the counterfactual women's employment rate in the economy with the added worker effect shut down. Monthly series smoothed using a 12-month moving average, adjusted for classification errors, corrected for time aggregation bias, HP-filtered with a smoothing parameter 1600 and presented averaged across quarters. Grey areas represent NBER recession periods.

The results are qualitatively similar to the original ones, although in the absence of changes in educational attainment we find higher levels of the AWE for all labor market outcomes except for women's unemployment. In absence of educational changes, the result that women's employment would look like men's in terms of volatility and skewness is preserved.

Table E.2: Added Worker Effect, Volatility and Skewness
(educational composition constant)

	Volatility	Cyclical Volatility	SD/SD_{GDP}	Skewness in levels	Skewness in growth rates
			Men		
Participation	0.17	0.03	0.11	-0.62	0.08
				[0.003]	[0.660]
Employment	0.71	0.56	0.45	-0.43	-1.18
				[0.031]	[0.000]
Unemployment	0.71	0.56	0.45	0.69	1.42
				[0.001]	[0.000]
			Women		
Participation	0.30	0.04	0.19	-1.10	-0.03
				[0.000]	[0.880]
Employment	0.42	0.23	0.27	-0.13	0.24
				[0.491]	[0.208]
Unemployment	0.51	0.40	0.33	0.19	0.80
				[0.335]	[0.000]
			Without the added-worker effect		
			Women		
Participation	0.95	0.06	0.61	-0.75	-0.77
				[0.000]	[0.000]
Employment	1.01	0.17	0.64	-0.49	-0.54
				[0.015]	[0.008]
Unemployment	0.48	0.35	0.30	-0.04	0.43
				[0.822]	[0.032]

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent standard deviations of the cyclical component, standard deviation of the predicted values of labor market states from the regression of cyclical component of labor state on cyclical component of log-GDP, ratios of standard deviations of the cyclical component of labor market state and cyclical component of GDP, skewness of cyclical component after HP-filtering ("in levels"), and skewness of the growth rates in the data and in the counterfactual steady state of the economy without an added-worker effect. P-values in brackets.

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