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' job loss. We propose a new method to calculate the AWE, which allows us to estimate its effect on any labor market outcome. We show that the AWE reduces the fraction of households with two non-employed members. The AWE also accounts for why women's employment is less cyclical and more symmetric compared to men. In recessions, while some women lose their employment, others enter the labor market and find jobs. This keeps the female employment relatively stable.

Keywords: 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 individuals between ages 25 and 54 who are in the labor force are married.[1] The growth of two-earner households was the result of married women's entry into the labor market since the 1950s. Only 35% of married women between the ages 25 to 54 were in the labor force in 1960. Today, about 73.7% 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 stocks are almost exclusively reported and analyzed using individual-level data.

Married-couple households, with two potential earners, can cope with adverse labor market shocks better than single-person households. If one household member gets an adverse employment or wage shock, the other member can adjust the labor supply to compensate. 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? 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), which is the main data source to study labor market dynamics in the U.S. We focus on the joint labor market states for two members of the household. There are nine such states, which expand the standard individual labor market states, i.e. employment (E), unemployment (U) and out-of-the-labor-force (O) states. 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). We calculate transitions of husbands and wives among these nine possible labor market states, a nine-by-nine transition matrix.

We then shut down transitions associated to the AWE, and recalculate counterfactual joint labor market stocks. For example, if we are calculating the AWE for women, we can ignore a transition like EO to UE, which indicates that the husband moves from E to U, i.e., loses his job, and the wife moves O to E, i.e., enters the labor force and finds a job. Once we have counterfactual joint labor market stocks, we can reconstruct any labor market outcome we

[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. About 62% of men who are in the labor force were married, while for women, the share was 60%.

[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).

would like to study for households or individuals. Hence, our 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 stocks by eliminating fluctuations in any particular transition(s) by setting it to its period mean. In our case, we set those transitions to zero, to completely eliminate the AWE in the counterfactual economy.

We find that the AWE increases the labor force participation of married women by about 2.17 percentage points for the period we study. The AWE has been increasing. For the 2010-2017 period, the increase in female labor force participation due to the AWE is 3.22 percentage points. We then look at how household and individual labor market stocks would be without the AWE. For households, we focus on the fraction with two members who are not employed. 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.

We then ask whether the AWE affects individual labor market stocks. We document two facts on the cyclical movements in employment for men and women. The first fact is well known. Women's employment is less cyclical (see Doepke and Tertilt (2016), Albanesi (2019) and Fukui, Nakamura, and Steinsson (2018)). 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.[3] Women's employment is, on the other hand, 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; 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, as some women lose their employment in a recession, others enter the labor force, find jobs, and keep the employment rate relatively stable.

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 the size of the added worker effect has been growing in recent decades. Second, our paper is related to the recent macroeconomics literature that builds models

[3] On the skewness of aggregate employment, see Ferraro (2018).

with two-earner households to study how households smooth idiosyncratic income shocks. Ortigueira and Siassi (2013), Birinci (2019), Guner, Kaygusuz, and Ventura (2019), and Wu and Krueger (2019) 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, e.g. Mankart and Oikonomou (2017), Choi and Valladares-Esteban (2020), Pilossoph and Wee (2019), and Wang (2019). Our work is also related to the papers that show how men and women differ in their labor market fluctuations and the implications of these differences for the aggregate economy, e.g., Albanesi and Şahin (2018), Albanesi (2019), Fukui, Nakamura, and Steinsson (2018), Ellieroth (2019), and Coskun and Dalgic (2020). In particular, we higlight one potential factor, the AWE, that can generate gender differences in labor market fluctuations. Finally, on 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 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.[4] We restrict the sample to all couples who report to be married

[4]We do this to avoid the end-point problems associated with the HP-filter. This partly reflects the fitting of a trend line symmetrically through the data. If the beginning and the end of the sample do not reflect

and living in the same household and who report that one of the two members of the couple is the head of the household. 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 members 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 the situation of a couple in which the husband is unemployed (U) and the wife is non-participant (O). Hence, any couple can be in 9 different *joint* labor market states (EE, EU, EO, UE, UU, UO, OE, OU, and OO).[5] 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.[6] 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 transition probabilities.[7] Finally, we seasonally adjust each monthly series using a 12-months moving average. For a better visualization for the figures, however, we aggregate monthly data into

similar points in the cycle, then the trend is pulled upwards or downwards towards the path of actual stocks for the first few and last few observations; see Giorno, Richardson, Roseveare, and van den Noord (1995).

[5] Throughout the paper we refer to the labor market states, labor market stocks, and transitions probabilities of married couples as *joint* labor market states, *joint* labor market stocks, and *joint* transition probabilities. This is in contrast to the more common *individual* labor market states (employment, unemployment, and out of the labor force), *individual* labor market stocks (employment, unemployment, and participation), and *individual* transition probabilities (E to E, E to U, ..., and O to O.)

[6] See Elsby, Hobijn, and Şahin (2015) for further discussion and robustness about this method to correct for measurement error.

[7] We provide further details on these adjustments in Appendix A.2.

quarterly frequency.[8]

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, $\pi^M_{i,j}$ and $\pi^W_{i,j}$, of men (M) and women (W), respectively. Finally, we use $\pi^M_{i,j|k,l}$ and $\pi^W_{i,j|k,l}$ to denote an individual transition from i to j conditional on that the spouse transits from k to l. For example, $\pi^W_{O,U|E,U}$ 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 over our sample period.

In these transitions we can see two key features. One is that there are significant gender differences in movements across labor market states. The other is how couples coordinate their labor supply behavior.[9]

In terms of gender differences, 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:

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

Men (women) are less (more) likely to transit to 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-

[8]Figure A.1 in Appendix A.1 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.

[9]In Table A.2 of Appendix A, we report the period average of unconditional transition matrices Π_t.

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 with a 11.26% probability as unemployed. 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 Average Labor Market Transitions of Married Couples

		Male employed			Male unemployed			Male OLF		
Female transitions		E	U	O	E	U	O	E	U	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

		Female employed			Female unemployed			Female OLF		
Male Transitions		E	U	O	E	U	O	E	U	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 table 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 table 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 to transit 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 the symmetric movement between spouses can have opposite effects on female employment. In a recession, for example, when both men and women lose their jobs, the AWE mitigates the decline in female employment. As women enter the labor force, some of them find jobs, which keeps aggregate female employment stable. At the same time, some women 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 lower the aggregate female employment. The same logic also applies to male employment.

4 The Added Worker Effect

In this section, we propose a new measure for the added worker effect. As it is noted by Lundberg (1985), joint transitions are key to understand the AWE. 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 who is 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. Hence, we can measure the added worker effect as the change in labor market stocks which result if these transition probabilities are set to zero.

To compute the effect of the added worker effect on the labor market stocks, we build on the methodology in Shimer (2012). We follow two steps. 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 other 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. Because the s_{ij} joint stocks computed from equation (1) are close to the ones in the data, Equation (1) provides a natural way to calculate the AWE.[10] Hence, the second step is to set all the transitions that are associated to the AWE to zero, and recalculate joint stocks, denote them by s_{ij}^{noAWE}, from Equation (1)[11]. 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. In calculating the effects of the AWE, we focus on unemployment, (U/P), employment, (E/L) and participation (P/L) rates where $P = E + U$ and L is total labor force, $L = P + O$.

The existing measures of the AWE focus exclusively on the entry of the women into the labor force that is associated to husband's job loss.[12] While our method can also compute the increase in participation, $P - P^{noAWE}$, due to the added worker effect, we are also able to compute how the added worker affects any other labor market stock.

Table 2 documents the contribution of the added worker, i.e. the difference between the data and the counterfactual time series without the added worker effect, between 1977 and 2017. For the entire period, the added worker effect increases female labor force participation by about 2.71 percentage points. Most of this increase is absorbed by higher employment. Without the AWE, the employment rate of married women would be 2.49 percentage points lower. 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 3.11 and 3.22 percentage points respectively. The effect of the added workers on unemployment is not negligible either. In the absence of added worker effect, the female unemployment rate would be about 0.15 percentage points lower for the 2010-2017 period (the unemployment rate of

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

[11] When we set a particular transition to zero, we assume that the households who experience that transition stay in their initial state. Alternatively, we could let husband (or wife) change their state and wife (or husband) stay out of the labor force. The results with this alternative assumption are very similar.

[12] See, for example, Stephens (2002), Juhn and Potter (2007), Mankart and Oikonomou (2016), Halla, Schmieder, and Weber (2018), and Bredtmann, Otten, and Rulff (2018).

women during this period was 4.03%).[13]

Table 2: Role of Added Worker Effect for Individual States

	1977-2017	1980-1990	1990-2000	2000-2010	2010-2017
All					
Participation Rate	1.78	1.62	1.61	2.06	2.14
Employment Rate	1.57	1.48	1.51	1.85	1.75
Unemployment Rate	0.19	0.14	0.07	0.17	0.36
Males					
Participation Rate	1.02	0.73	1.04	1.23	1.31
Employment Rate	1.01	0.92	1.09	1.19	1.04
Unemployment Rate	-0.02	-0.22	-0.08	0.00	0.25
Females					
Participation Rate	2.71	2.62	2.31	3.11	3.22
Employment Rate	2.49	2.31	2.21	2.94	2.98
Unemployment Rate	0.18	0.30	0.04	0.09	0.15

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 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. 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 upper panel we shut down all aforementioned transitions (the added worker effect for males and females).

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 2010-2017 period, the participation of men increases by 1.31 percentage points (the participation rate of men during this period was 93.61%). While for women almost all the increase in the participation is absorbed by employment, for men about 20% of the increase in the labor force participation results in higher unemployment.[14]

[13] Figure B.2 in Appendix B presents added worker effect as the difference between the data and the counterfactual series for the unemployment, employment, and participation rates.

[14] Table B.1 in Appendix B presents the effects of the AWE for recessions and expansions. The AWE is a bit more important for employment during recessions, while it is more important for unemployment in expansions. In the case of unemployment, male's added worker effect is negative during recessions, that means that males do not enter more from out of the labor force to unemployment if their wife loses her job. 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. In other words, men enter unemployment mostly from employment, not from non-participation.

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 the households. Since 1976, US households changed dramatically. There has been a significant decline in the number of traditional households who are in *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 these 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), which coincides with the decline in aggregate labor force participation.[15] 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.[16]

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.[17]

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 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*. On average, 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 in the counterfactual economy 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

[15] For an analysis of the decline in the US labor force, see, among others, Krueger (2017).

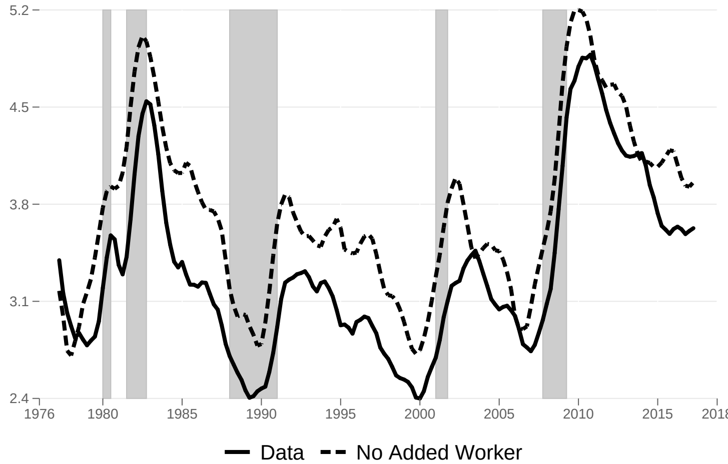
[16] The solid lines in Figure B.1 in Appendix B present the joint labor market stocks.

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

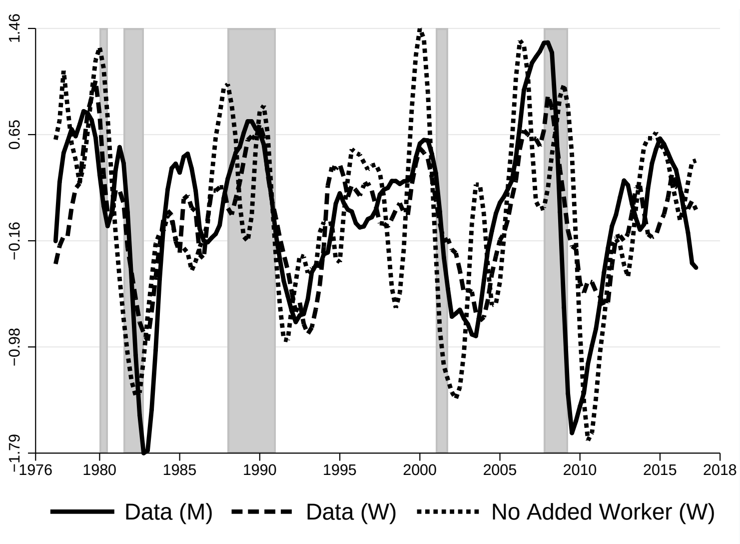
points higher. This is about 16% of households without any employed members. We see this measure as a conservative indicator of how the AWE affects households since it abstracts from adjustments along the intensive margin.

Figure 1: Households and the Added Worker Effect

(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.

5.1 Individuals: Women are Different

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.[18] 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. The volatility of employment for women is 0.43, while it is 0.64 for men (Table 3).

The second fact is novel. Men and women also differ in asymmetry (or skewness) of their employment fluctuations. For asymmetry, we follow Sichel (1993) and Ferraro (2018) and report two measures. The first is the deepness asymmetry, which measures the skewness of the cyclical components of a series. If a series is symmetric in deepness, 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 steepness asymmetry, which measures the skewness in growth rates. If a series has symmetry in steepness, expansions and recessions are associated with similar growth 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. Employment is negatively skewed for men (skewness in levels is -0.60 and skewness in growth rate is -1.18). Hence men experience more significant drops in employment during recessions, followed by slow recoveries in expansions. Indeed, the aggregate employment also shows negative skewness.[19] This is, however, not the case for women. Women' employment behavior is symmetric in level (skewness is, basically, zero).

In terms of skewness in growth rates, women employment grows marginally faster than it falls (skewness in growth rates is 0.38). Unemployment displays positive skewness in levels, i.e., peaks during recessions are larger than troughs during expansions. The skewness is, however, almost twice as high for men as it is for women (0.80 vs. 0.47). The pattern also emerges in growth rates (1.32 vs. 0.62). 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 times (steepness skewness is 0.48).

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

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

[19] See Ferraro (2018) for an analysis.

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 (0.70 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 (-0.32) and in steepness (-0.38).

Table 3: Standard deviation and Skewness for Individual Stocks

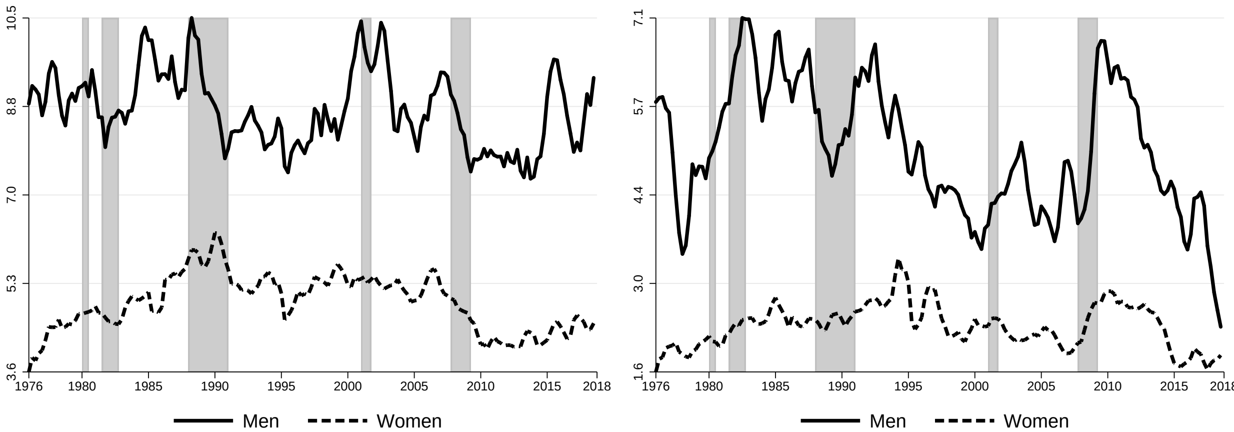
	Volatility	Skewness Deepness	Skewness Steepness
		Men	
Participation	0.11	-0.14	0.17
		(0.458)	(0.355)
Employment	0.64	-0.60	-1.18
		(0.003)	(0.000)
Unemployment	0.63	0.80	1.32
		(0.000)	(0.000)
		Women	
Participation	0.24	0.08	0.48
		(0.684)	(0.013)
Employment	0.43	-0.12	0.38
		(0.528)	(0.047)
Unemployment	0.45	0.47	0.62
		(0.015)	(0.002)
		Without the added-worker effect	
		Women	
Employment	0.70	-0.32	-0.40
		(0.094)	(0.036)

NOTE: CPS 1977:Q2 to 2017:Q3. All individuals aged 25-54. The numbers in the table represent standard deviations of the cyclical component, skewness of cyclical component after HP-filtering ("Deepness"), and skewness of the growth rates ("Steepness") in the data and in the counterfactual steady state of the economy without an added-worker effect. P-values in parenthesis.

Why does women's employment in a world 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 to 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 increase for women in the 1990 recession. Furthermore, O to U transition, which increases significantly for men in each recession, are also much more stable for women.

Figure 2: Individual Labor Market Transitions of Males and Females

(a) O-E (b) O-U



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. Grey areas represent NBER recession periods. 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.

6 Conclusions

We propose a new method to measure the added worker effect based on the joint transition probabilities of married households across labor market states. The main advantage of our method is that it offers a transparent procedure to assess the importance of the added worker effect on any labor market outcome.

We document three key facts. First, the role of the added worker effect in determining the participation, employment, and unemployment rates of both men and women has grown over the last four decades. If there are more women in the labor force, then there is less of them in O state. Then we should expect that there is a smaller pool of women who can enter. Second, 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 potentially negative labor market outcomes. Thirdly, 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 also negatively skewed.

The secular changes in terms of family and the role of women of the last decades have crucially changed many aspects of the economy. Our results single out one mechanism, the added worker effect, to assess how household labor supply affects labor market aggregates and the amount of insurance in the economy provided by households.

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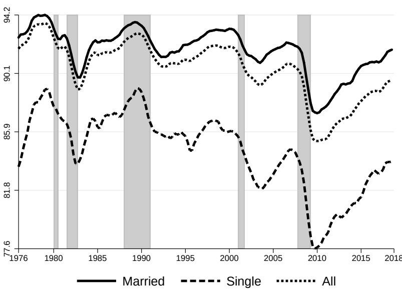
Appendix A: Data

A.1 Labor Market Stocks of Single, Married and All Individuals

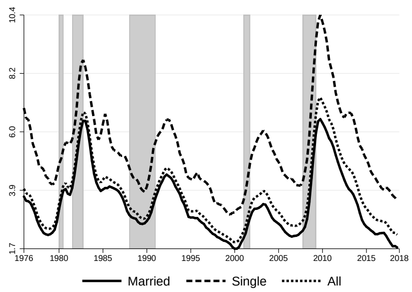
In this subsection we show the unemployment, (U/P), employment, (E/L) and participation (P/L) rates for married, single, and all individuals, where $P = E + U$ and total population is $L = P + O$.

Figure A.1: Labor Market Stocks of Single, Married and All Individuals

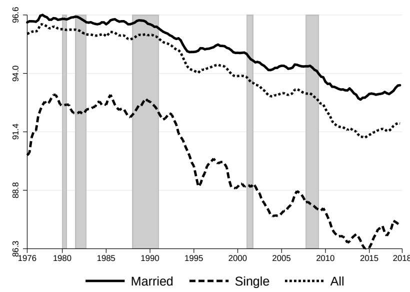
(a) Participation - Men



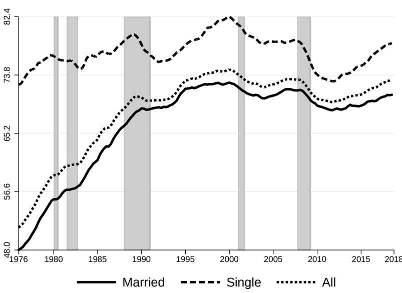
(b) Employment - Men



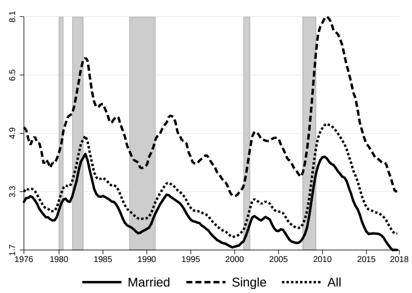
(c) Unemployment - Men



(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.2 Data Correction Details

A.2.1 Classification Errors

In this section of the Appendix, we provide details on adjustments for classification erors and time aggregation bias. The 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 recode 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 recode them. In Table A.1 we report all the transitions that are recoded. The difference between 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 recoding 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.2 (men) and Figure A.3 (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.2.2 Time Aggregation Bias

The 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.[20]

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):

[20] Describing the procedure below, we closely follow working paper version of Elsby, Hobijn, and Şahin (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}
$$

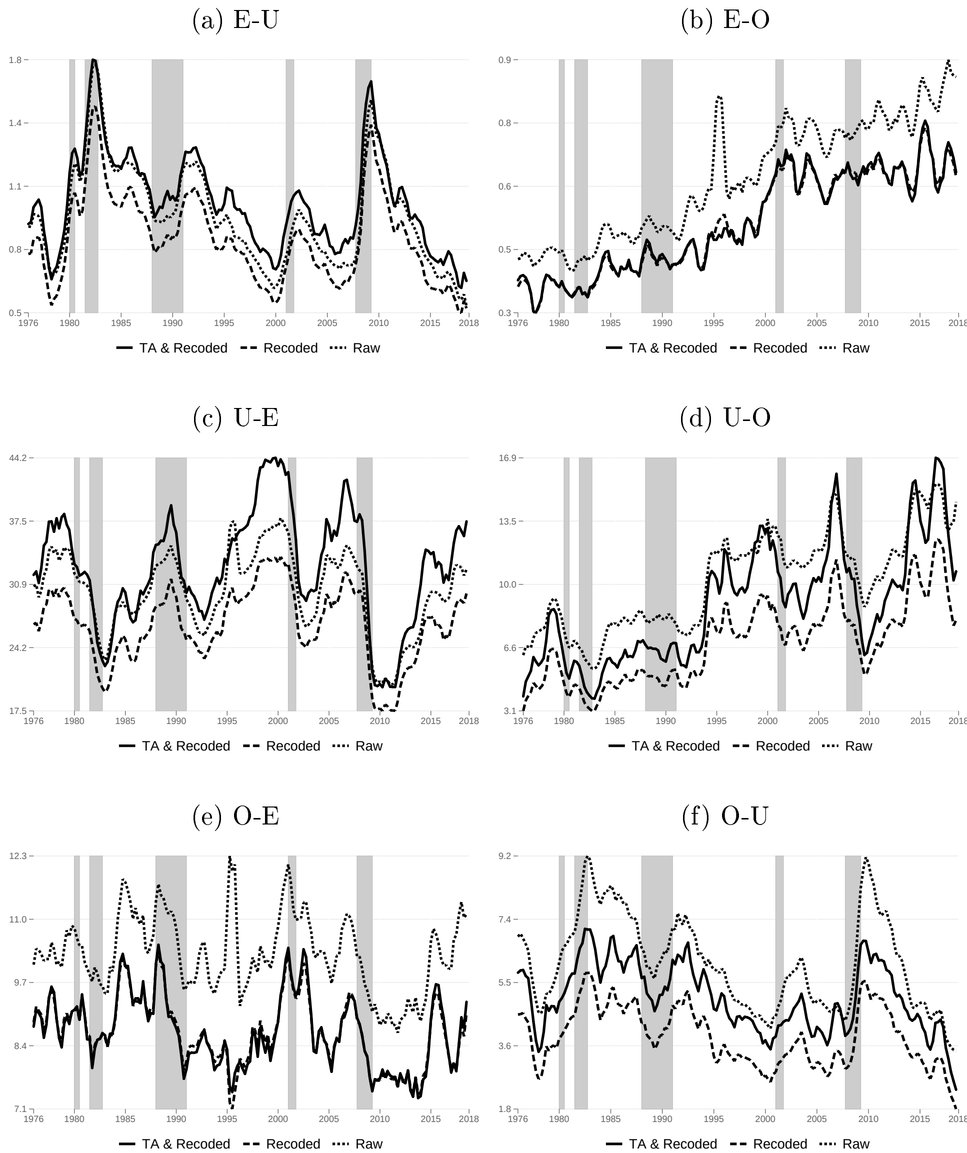
Analogous continuous time equation to this Markov chain is $\dot{s}_t = \Pi_t s_t + q_t$, where q_t is continous-time version of g_t. From discreet-time version, $s_t = \Gamma_t s_{t-1} + g_t$ we find the steady state of the discrete Markov chain by $\overline{s}_t = (I - \Gamma_t)^{-1} g_t$. The steady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

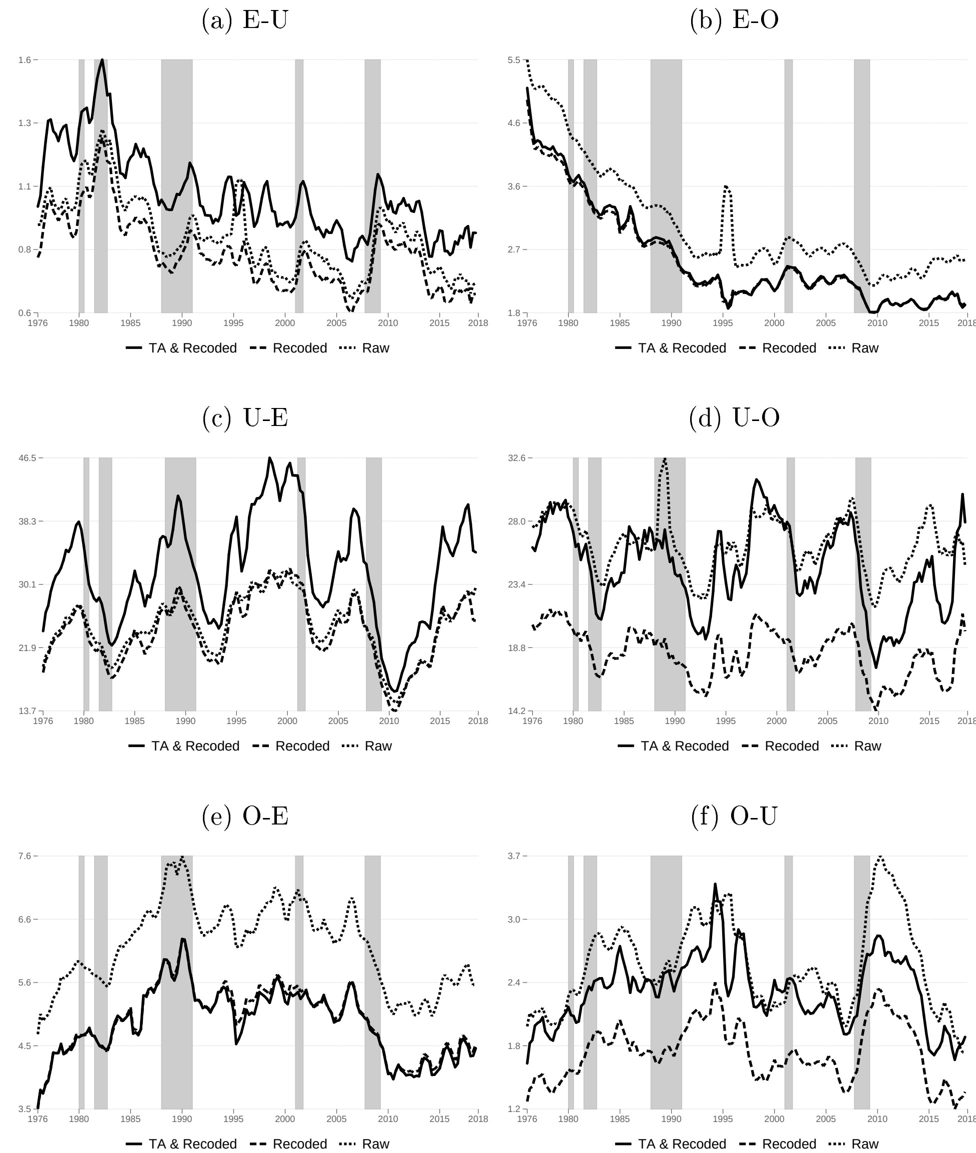
In Figure A.2 and Figure A.3 we present estimates of labor market flows that are adjusted for the time aggregation (after correction for the classification errors), together with the raw flows and flows that are adjusted for the classification errors. The effect of time-aggregation bias is minimal on 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 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.

Figure A.3: 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.3 Joint Labor Market Transitions of Married Couples

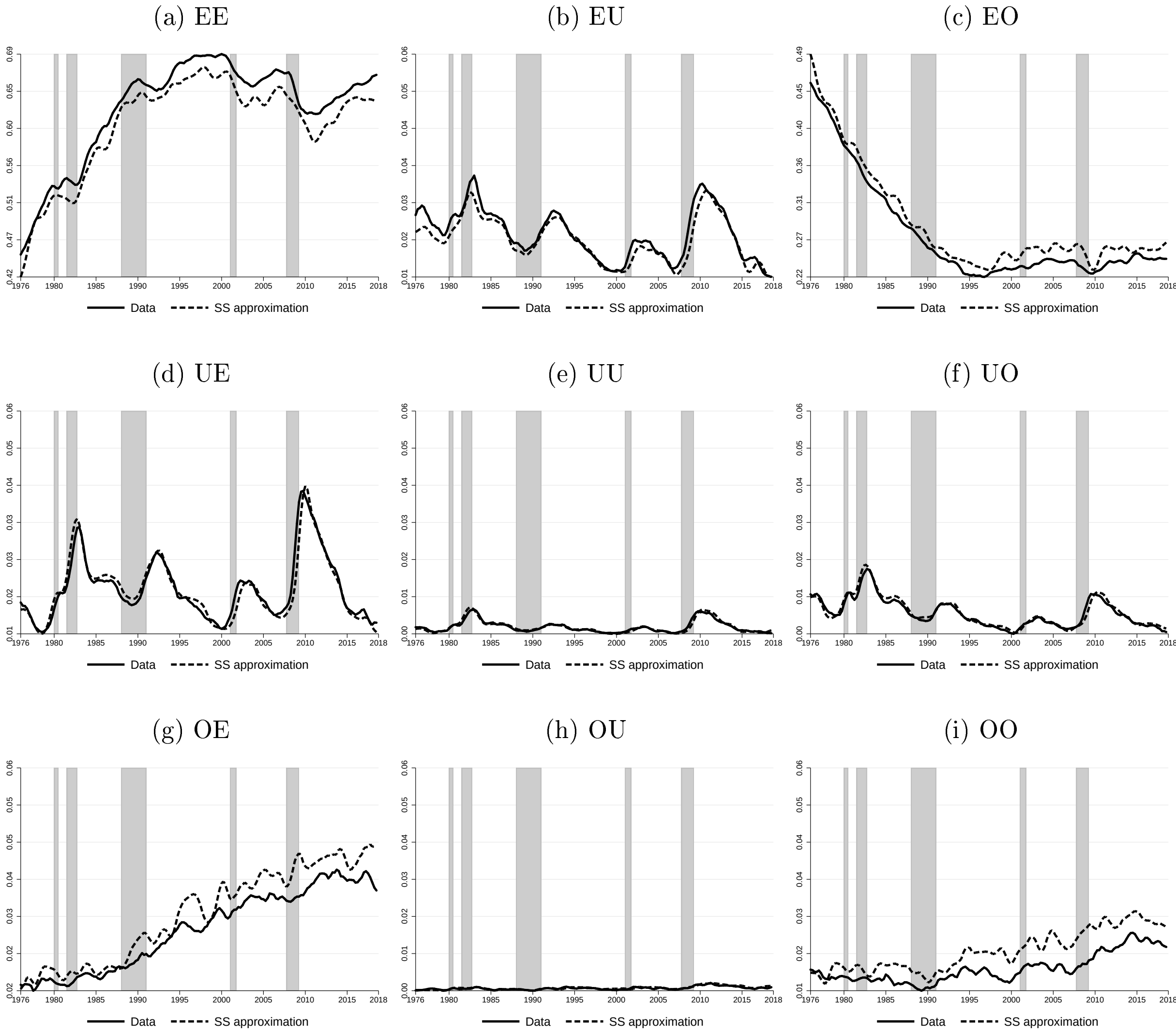
Table A.2: Joint Average Labor Market Transitions of Married Couples

	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

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. Grey areas represent NBER recessions. 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.

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. Grey areas represent NBER recession periods. 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.

Table B.1: Role of Added Worker Effect for Individual States of Married People During Expansions and Recessions

	Expansions						
	1977Q2 1979Q4	1980Q4 1981Q2	1983Q1 1987Q4	1991Q2 2000Q4	2002Q1 2007Q3	2009Q3 2017Q3	Total
All							
Participation Rate	1.07	1.69	1.72	1.65	1.93	2.13	1.78
Employment Rate	0.80	1.53	1.48	1.51	1.70	1.75	1.54
Unemployment Rate	0.36	0.15	0.25	0.10	0.21	0.36	0.23
Males							
Participation Rate	0.41	0.57	0.73	0.99	1.03	1.19	0.95
Employment Rate	0.23	0.60	0.72	0.90	0.81	0.75	0.75
Unemployment Rate	0.18	-0.05	-0.02	0.06	0.21	0.42	0.17
Females							
Participation Rate	1.73	2.81	2.70	2.30	2.83	3.08	2.62
Employment Rate	1.36	2.46	2.24	2.13	2.59	2.74	2.33
Unemployment Rate	0.54	0.36	0.51	0.14	0.20	0.30	0.29

	Recessions					
	1980Q1 1980Q3	1981Q3 1982Q4	1988Q1 1991Q1	2001Q1 2001Q4	2007Q4 2009Q2	Total
All						
Participation Rate	1.24	2.04	1.36	2.47	2.13	1.77
Employment Rate	1.07	1.98	1.35	2.38	2.04	1.71
Unemployment Rate	0.24	0.02	-0.02	0.03	0.03	0.03
Males						
Participation Rate	0.71	0.50	0.78	1.02	1.55	0.92
Employment Rate	0.79	0.84	0.93	0.99	1.56	1.04
Unemployment Rate	-0.11	-0.38	-0.18	0.00	-0.07	-0.16
Females						
Participation Rate	1.77	3.58	1.93	3.92	2.70	2.62
Employment Rate	1.34	3.12	1.77	3.77	2.52	2.38
Unemployment Rate	0.60	0.41	0.14	0.06	0.13	0.22

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: References in Appendix

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