Is There Still an Added Worker Effect?[1]

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Abstract: Using matched March CPS files we examine labor market transitions of husbands and wives. We find that the "added worker effect"—the greater propensity of non-participating wives to enter the labor force when their husbands exit employment—is still important among a subset of couples but the overall value of marriage as a risk-sharing arrangement has diminished due to the greater positive co-movement of employment within couples. While we find that positive assortative matching on education did increase over time, we find that this shift in composition of couple types alone explains little of the increased positive correlation.

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I. Introduction

One potential benefit of marriage is that it provides opportunities for risk-sharing. For example, if the husband suddenly becomes unemployed or ill, the wife may enter the labor force to make up for the loss in family income—a phenomenon labor economists have labeled the "added worker effect." The need for or the feasibility of intra-family risk-sharing, however, depends on market conditions, as well as changing characteristics of marriage.[1] To the extent that state-provided unemployment insurance presents a feasible alternative, the family may play a lesser role in smoothing income fluctuations. If private credit and insurance markets function perfectly, the family may also turn to these market alternatives rather than to its own smoothing mechanisms. Indeed, in a life-cycle model with perfect certainty and no credit market constraints, variations in a husband's earnings should have little effect on the wife's labor supply.[2] The added worker effect may be sizeable, however, if either of the two conditions fails.[3]

There are reasons to suspect that the value of marriage as a risk-sharing arrangement has diminished over the past several decades in the U.S. Social insurance such as unemployment or disability benefits may have "crowded out" spousal labor supply along the lines suggested by Cullen and Gruber (2000). Unilateral divorce laws and the weakening of the institution of marriage may have reduced the intrinsic ability of the family to enforce risk sharing contracts (Pollack (1985)). In an environment in

[1] See Weiss (1997) for a review of the economic benefits of marriage and a discussion of how the gains from marriage depend on market conditions.
[2] Supporting this theoretical prediction, Heckman and MaCurdy (1980) find little impact of a husband's unemployment spell on the wife's annual hours worked.
[3] With uncertainty, a husband's employment loss may lead households to downwardly adjust their permanent income forecasts, causing the wife to increase her labor supply. Stephens (2004) explores these effects and finds a larger added worker effect.

which divorce is both legally and socially accepted, partners may be less willing to insure each other's income shocks.

The value of marriage as an insurance mechanism also decreases if the underlying labor market shocks of spouses become more positively correlated. Couples have always looked similar in terms of education (see Mare (1991)). However, this underlying positive assortative mating did not used to be so apparent in the labor market, as a significant fraction of married women remained in the home. Since 1960 married women's labor force participation rate has doubled from 30 percent to over 60 percent (Blau, Ferber, and Winkler (2005)).[4] In addition, their labor force attachment has increased, as evidenced by the rise in average experience level (Blau and Kahn (1997)). Labor market shocks of husbands and wives are likely to become more positively correlated as married women become more strongly attached to the labor force and make investments similar to their husbands'. The fundamental question we ask in this paper is whether these shifts—particularly shifts in married women's long-run work behavior—have impacted the "added worker effect" and, more generally, the co-movement of couples' employment.

We use March Current Population Survey files matched across adjacent years to examine whether labor market transitions of husbands and wives are jointly determined. We find evidence of the "added worker effect" in that a non-participating wife is five to six percentage points more likely to enter the labor force if the husband exits employment than if the husband remains employed. While this compensatory behavior still exists, it has a smaller impact on the overall correlation of couples' employment changes since the pool of non-participating wives has shrunk over time. Using information on all labor

[4].The statistic refers to married women who are 14 and older with a husband present in the household.

market transitions between three states—employment, unemployment, and out of the labor force—we simulate the steady-state level of employment using the joint probability transition matrix of husbands and wives. We compare this to the level simulated assuming independence between spouses' labor market transitions. Our simulation results suggest that employment is lower in 1968 when we use the joint matrix than when we use the independent matrix, implying couples' employment changes were negatively related. In 2005, however, employment is higher using the joint matrix, suggesting a positive relationship. The positive co-movement of couples' employment points to a diminished role for intra-family risk-sharing. While we find that positive assortative matching on education did increase over time, this shift in composition of couple types alone explains little of the increased positive correlation. We also examine how intra-family employment dynamics affect aggregate fluctuations in employment over the business cycle. We find that the negative dependence of couples' labor market transitions had a dampening effect on aggregate employment fluctuations in the 1960s and the 1970s, but the dampening effect disappeared by the 1990s and the 2000s.

Our paper is closely related to papers on individual and family earnings dynamics (Abowd and Card (1989), Hyslop (2001), Shore (2006)). Hyslop (2001), using the Panel Study of Income Dynamics, finds that the cross-correlation of couples' earnings is lower than that of couples' wages, suggesting compensatory labor supply behavior. He focuses on continuously employed married couples, however, and does not examine labor supply at the extensive margin, which is what our focus is. Shore (2006) also uses the PSID and finds that innovations to spouses' incomes have a negative correlation of 10 percent, on average. While our paper is a useful complement to these papers on earnings dynamics, it also makes unique contributions on several fronts. It uses a different data set—the matched March Current Population Surveys—and focuses on labor market transitions rather than earnings. Reported labor market transitions, such as the movement from employment to unemployment, are less likely to be measured with error than innovations in hours or earnings. Unlike these previous papers, our focus is not only to establish that spouses' earnings move positively or negatively together, but also to examine if and why the correlation has changed over time.

Our paper is also closely related to papers on the added worker effect. Lundberg (1985) uses data from the 1969-73 Seattle and Denver Income Maintenance Experiment to estimate labor market transition rates of couples and uses these estimates to simulate levels of unemployment and employment. She finds a small positive impact of husbands' unemployment on wives' labor force participation. While similar, the advantage of our analysis is that we use a larger, more representative sample of matched husbands and wives spanning a long time period. This allows us to examine to what extent the correlation of spouses' labor market transitions have shifted over time, as well as how they may differ across recessions and expansions.[5]

Our paper is structured as follows. We describe our data in the next section. Section 3 describes labor market transitions, giving particular attention to the added worker effect. Section 4 details our empirical methods and presents our main results. Section 5 concludes.

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[5] Spletzer (1997) also uses transition rates from matched monthly Current Population Surveys for 1988-89 and 1990-91. The paper documents substantial contemporaneous correlation between husbands' entry into unemployment and wives' entry into the labor force. Compared to Spletzer (1997), we use a much longer period in our paper and characterize recessions versus expansions. We also incorporate information on all labor market transitions to conduct simulations to compare employment levels.

II. The Data

We use the March[6] CPS files to match husbands and wives for each year from 1968 to 2005. We then match couples' first interviews to their records in the following year, using gender, race, and age to exclude potentially invalid matches, following the algorithm suggested in Madrian and Lefgien (1999). We match husbands and wives using marital status, household identifier, household type and relation of individuals to the household head. Our current sample does not attempt to match across potential cohabitants. Using this method, we match over 97% of individuals who report to be married and living with a spouse. We focus our analysis on households in which the husband is between 22 and 54 years of age. Although we allow older and younger women in the data in principle, in practice there are very few observations for which the age of the wife is outside the 22-54 age range. Our data consists of 224,359 husband-wife pairs that could be matched across spouses and across years. Details of the construction of our matched sample are in Appendix A.

We define the three labor market states—employed (E), unemployed (U), and out of the labor force (O)—based on employment status last week. We categorize each set of two adjacent years into one of four categories based on aggregate economic condition: 1) expansion/expansion, 2) expansion/recession, 3) recession/recession, and 4) recession/expansion. Our classification of the business cycle phase is similar to the NBER classification of recessions and expansions, with the exception that we allow for the possible lagging behavior of the labor market and date the end of the recession as the

[6]Using everyone interviewed in March of a given year, the CPS compiles the Annual Social and Economic Supplement (called the Annual Demographic File through 2002).

point at which the unemployment rate stops increasing. Table 1 shows our classification of each set of adjacent years since 1968.

III. Labor Market Transitions

A. Labor Market Transitions

Table 2a shows husbands' labor market transitions separately for the four states of the aggregate economy. The table highlights the fact that most prime-aged men are and remain employed. For example, during expansion/expansion periods, 96.8 percent of employed men remain employed the following year. The transition from employment to unemployment is higher during periods involving recessions, and particularly high during expansion/recession periods, in which job destruction is most prevalent.

Table 2b presents a similar breakdown of wives' labor market transitions. The table shows that a considerable fraction of women who are out of the labor force in year *t* are in the labor force the following year. For example, during expansion/expansion periods, 19.9 percent of non-participants (17.9 percent of employed and 2.0 percent of unemployed) were in the labor force the following year. Also notable is that a large fraction of unemployed women leave the labor force, a phenomenon usually labeled as the "discouraged worker effect." Even during expansion/expansion periods, 30.5 percent of unemployed women leave the labor force. This fraction is largest during periods of prolonged downturns (i.e. recession/recession periods).

B. The Added Worker Effect

We are interested in wives' labor market transitions (a 3x3 matrix) interacted with each possible labor market transition of the husband, which results in a 9x9 matrix. In the next section we use information on all transitions to assess the overall correlation of couples' employment changes. In this section, however, we focus on one particular transition that has received a great deal of attention in the labor literature—the added worker effect. The added worker effect applies to couples in which the husband is employed and the wife is out of the labor force in year *t*. In our sample, this consists of 69,608 couple observations. We label husbands' employment probability as E_t^m and their non-employment probability, which is the sum of their unemployment and non-participation probabilities, as N_t^m. We label wives' probability of being out of the labor force as O_t^f and their probability of being in the labor force, which is the sum of their employment and unemployment probabilities, as L_t^f. We compare the probability of entering the labor force among wives whose husbands exit employment, $E_t^m N_{t+1}^m$, to the same probability among wives whose husbands remain in employment, $E_t^m E_{t+1}^m$, and label it as (our version of) the added worker effect, *AWE*.

$$AWE = P[L_{t+1}^f / E_t^m N_{t+1}^m, O_t^f] - P[L_{t+1}^f / E_t^m E_{t+1}^m, O_t^f]$$

Table 3 reports wives' probabilities of entering the labor force by husbands' labor market transitions. Again, we group years as described in Table 1. During expansion/expansion periods, 21.6 percent of wives whose husbands exited employment became employed, and 4.2 percent became unemployed. Among wives whose husbands remained employed, 18.2 percent became employed, and 1.8 percent became unemployed. The last column shows the difference in entry rates between the two groups, which is 5.8 percentage points. The difference is more pronounced when the economy moves from an expansion to a recession. During these periods, the difference in entry rates between wives whose husbands exited employment and wives whose husbands remained employed is 9.4 percentage points.

In Table 4, we go one step further by examining whether this difference is due to observable characteristics of the wife, the husband, or the household. We also examine whether the coefficients on these characteristics, as well as the overall effect of a husband's exit from employment, increases or decreases over time. We estimate a simple probit, controlling for wife's age and education, husbands' education, the total number of children, and an indicator variable, "birth," which is turned on if the number of children increases over the year.

Table 4 reports the increase in marginal probabilities associated with each independent variable, as well as the associated standard errors. The estimated effects accord with intuitive expectations. For example, the better educated the wife, the more likely she is to enter the labor force. Interestingly, the husband's college education has a significant negative impact when we control for wife's own education, but the effect is no longer significant by 2004-05. Both children variables have significant negative impacts on the probability of entry. The last row in Table 4 shows that a husband's exit from employment increases the probability of the wife entering the labor force by 5.6 percentage points. The interaction variables show that this effect is largest during expansion/recession periods. Comparing 1968 and 1973 (the "earlier period") and 2004 and 2005 (the "later period"), the impact of husband's exit, our added worker effect, actually increases from .042 to .082.

The added worker effect described above focuses on couples in which the husband is employed and the wife is out of the labor force in year *t*. This group as a whole became a smaller fraction of couples over time as married women increased their labor market participation. As shown in Table 5, 53.4 percent of couples had an employed husband and non-participating wife in 1968 and 1973 (the earliest expansionary periods). By 2004 and 2005, only 22 percent of couples fell into this category. While the added worker effect still exists in the later years, then, it is unlikely to be relevant since couples in which both the husband and the wife are working in a given year became the majority. In results we do not report here, we also found that other labor market transitions have changed to counteract the added worker effect. Among couples in which the husband is employed and the wife is in the labor force in year *t*, for example, the wife's probability of leaving the labor force is greater if the husband also leaves employment. This effect has become stronger over time. In the next section, we develop empirical methods to incorporate information on all labor market transitions to examine the overall co-movement of couples' employment.

IV. The Co-Movement of Couples' Employment

A. Interpretation and Estimation of Transition Matrices

In our dataset, we can observe individuals' transitions across three employment states—employment(E), unemployment (U), and out of the labor force (O)—resulting in a 3x3 transition matrix with elements λ_{ij}, where *i* refers to the labor market state in year *t*, and *j* refers to the labor market state in year *t+1*. Interacting husbands' and wives' employment states, couples can cycle across nine joint employment states, which produces a 9x9 joint transition matrix, Λ.

The joint transition matrix contains a variety of information on how individuals react to their spouse's labor market status, whereas the smaller, individual transition matrices (the 3x3 ones) ignore the spouse's labor market status. It is possible to use the joint transition matrix to estimate individual transition matrices by averaging over spouse's labor market status. We use this fact to build an alternative metric of the dependence in spousal labor supply. The metric is the difference between the joint transition matrix and an "independent" transition matrix, $\tilde{\Lambda}$, which we construct by assuming independence between spouses' labor supplies. We obtain the independent transition matrix by taking the Kronecker product of the estimated individual transition matrices.

We then find the equilibrium distribution for the joint and independent transition matrices in order to construct the "equilibrium" employment-population ratio for couples and other standard measures of the labor market. We do all of the analysis in this and the following section for both the joint and the independent matrices; however, for simplicity, we describe only that for the joint transition matrix.

The notion of "equilibrium" has two interpretations: at the individual level, it is the probability distribution across employment states after the effects of initial conditions have worn off; at the aggregate level, it is a situation in which the flows of married couples across states exactly balance. Thus, if we estimate one transition matrix for all married couples that is fixed over time, we would be forced to view any changes as a convergence to an equilibrium in which aggregate labor market states were constant.

To avoid this restriction, we allow the transition matrix to vary across time, business cycle phases, and married couples' characteristics. We have already discussed differences across business cycle phases and associate the four phases with four different transition matrices: expansion/expansion (Λ^{EE}), expansion/recession (Λ^{ER}), recession/recession (Λ^{RR}), and recession/expansion (Λ^{RE}).

We could use many characteristics to group married couples; however, we are most interested in their education level. Thus, for each business cycle phase, we create 16 transitions matrices, one for each of the 16 possible education pairings. (We call these matrices Λ_g^{BC}, where *g* takes values from one to 16 and *BC* is one of the four business cycle abbreviations, above). Our crucial identification assumption is that, given our segmentation of the data into different business cycle phases and education groups, employment transitions are independent across households. That is, given a business cycle phase and an education group, one household's change in labor market status provides no information about another household's change.

Under this identification assumption, fluctuations in aggregate labor market behavior can be produced by switching between business cycle phases and by changing the composition of couples' education groupings. In addition to these factors, we also want to relax the restriction that, for a given education group and business cycle phase, the transition matrix has been invariant over time. In particular, we are interested in changes in the way wives react to their husband's labor market status.

We use a Bayesian procedure to estimate the transition matrices (that is described in more detail in Appendix B). For the issues we are interested in a Bayesian procedure has a number of advantages over standard maximum likelihood approaches to estimating transition matrices. In both Bayesian and MLE approaches, the basic set of observations are the normalized counts of the number of transitions. If we estimated one transition matrix for our whole sample (i.e. if we did not allow the transition matrices to vary by business cycle phase, education grouping, and time), the two approaches would produce identical results. The way we are splitting the sample, however, gives us many joint labor market states that have no observations in one or more of the transition matrices. By adding a small amount of prior information, the Bayesian approach allows us to still estimate a valid transition matrix in those cases.

If our interest was directly in the labor market state(s) with no observations, little would be gained from using the prior information. Our focus, however, is on making inferences on aggregate variables, such as the employment-to-population ratio. As discussed above, this is a feature of the whole transition matrix. In addition, we want to compare results from the joint transition matrix with the independent matrix. In order to perform inference on the differences between the results, we need to generate draws of valid transition matrices that take into account the amount of sample information in the estimate. Bayesian methods allow us to do this much more easily than maximum likelihood methods.

Finally we need a method to allow for time variation. The crudest approach would to estimate separate matrices for each year in our sample. The most sophisticated approach would be to model the time variation directly, which would require a substantial increase in computational complexity. We take a middle ground between these two approaches and discount years by their distance from the year of interest. We focus on the years at the start and end of our sample (1968 and 2005) and weight transitions in years close to 1968 more heavily than those in years close to 2005, and vice versa, and label these estimates "1968-weighted" and "2005-weighted" estimates, respectively.[7]

B. Simulation of Employment Levels

We simulate employment-population ratios in the following manner. We start by assuming the economy has been in the expansion state for a sufficiently long time, such that the flows into and out of each labor market state are equal. In other words, for each education group, we solve for the equilibrium probabilities π given by the transition matrices Λ^{EE}. We call this "continued expansion." For each education group, we then run the economy through the following sequence:

- A move from expansion to recession. In this case, we calculate the transitions using the transition matrix Λ^{ER}, with time t probabilities given by π, and the employment-population using $\Lambda^{ER}{}'\pi$.
- A move from recession to recession. In this case, we calculate the transitions using the transition matrix Λ^{RR}, with time t probabilities given by $\Lambda^{ER}{}'\pi$, and the employment-population ratio using $\Lambda^{RR}{}'\Lambda^{ER}{}'\pi$.

[7] The discounting of observations in the second and third approach is a simple way of estimating a time-varying parameter model (see West and Harrison 1997). See Appendix B for details.

- A move from recession to expansion. In this case we calculate the transitions using the transition matrix Λ^{RE}, with time t probabilities given by $\Lambda^{RR}{}'\Lambda^{ER}{}'\pi$, and the employment-population ratio using $\Lambda^{RE}{}'\Lambda^{RR}{}'\Lambda^{ER}{}'\pi$.

Recall that, for each education group and business cycle phase, we have both joint and independent transition matrices, and, for both of these matrices, we have two different estimates, one weighted towards 1968 (Λ^{1968}) and one weighted towards 2005 (Λ^{2005}). For each education group, then, we run the above simulation for both the joint and independent matrices and for both estimates. Finally, we use 10,000 draws from the set of posterior distributions and form averages across these draws for each education pairing. We then use each education group's population weights to form aggregate employment-to-population ratios for both types of matrices and both estimates.

Table 6 shows our predicted employment-population ratios using the joint transition matrix, Λ, and the hypothetical, independent matrix, $\tilde{\Lambda}$. For completeness, we also simulated unemployment rates and labor force participate rates and report them in Appendix Tables 3 and 4. The columns in Table 6 display the evolution of the employment-population ratio as we move through the four business cycles: expansion/expansion (column 1), expansion/recession (column 2), recession/recession (column 3), and recession/expansion (column 4).[8]

The top row uses the 1968-weighted estimates, Λ^{1968} and $\tilde{\Lambda}^{1968}$. According to column (1), the steady-state employment-population ratio is lower (74.2) using the joint matrix than using the independent matrix (74.2 vs. 75.9). This suggests that husbands'

[8] We have included posterior standard deviations under each prediction. These indicate the precision of each estimate, but cannot be directly used to calculate the statistical significance of the difference between the joint and independent predictions.

and wives' labor market transitions were negatively related in 1968. In contrast, the steady-state employment-population ratio using the 2005-weighted estimates, Λ^{2005} and $\tilde{\Lambda}^{2005}$ (row 2), show positive correlation. For example, we predict the employment-population ratio to be 81.8 under the independence assumption. It is actually *higher* (83.2) using the joint matrix.

Examining the posterior density functions of the difference between the joint and independent estimates (i.e. joint minus independent) for 1968 and 2005 for the four business cycle phases shows that both the 1968 and the 2005 differences are statistically significant. The four panels in Figure 1 illustrate these functions for the four business cycle phases. For example, in Figure 1A, which focuses on the expansion/expansion phase, we see that the change in spousal dependence from a negative to a positive relationship is statistically significant. Specifically, the probability that the joint estimates are smaller than the independent estimates is 93 percent in 1968. In contrast, the probability that the joint estimates are larger than the independent estimates is 97 percent in 2005. Our 1968 estimates are less precise because of the smaller effective sample size in the earlier part of our data due to missing years in the 1970s.

We next examine employment dynamics over the business cycle. Reading across the top row of Table 6 which examines predictions using 1968-weighted estimates, we find that fluctuations in the employment-population ratio are smaller using the joint matrix than using the independent matrix. From the expansion to the depth of the recession (row (1) columns (1) and (3)), the employment-population ratio falls approximately one percentage point, from 74.2 to 73.1. If we assume independence between spouses, however, the ratio falls 2.3 percentage points, from 75.9 to 73.6. This suggests that spouses' negative dependence had a smoothing effect on employment fluctuations over the business cycle in the earlier period. In 2005, the joint and independent estimates predict similar changes in aggregate employment over the business cycle. Comparing again the change from the expansion to the second year of the recession (row (2), columns (1) and (3)), we find the employment-population ratio fell 1.8 percentage points allowing for joint-ness and 2.0 percentage points under independence.

To summarize, we simulate aggregate employment-population ratios using the couples' joint transition matrix, as well as a hypothetical transition matrix that enforces independence. Using 1968-weighted estimates, we find that labor market transitions of husbands and wives were negatively related and that this negative correlation had a smoothing effect on aggregate employment over the business cycle. In contrast, when we use 2005 estimates, we find that labor market transitions of spouses are positively related and that the smoothing effect over the business cycle has largely disappeared.

C. The Role of Positive Assortative Mating on Education

In this section, we explore to what extent the rising prevalence of more educated couples and positive assortative mating on education contributed to the emerging positive correlation of spouses' employment. We first examine changes in the distribution of couple types in the beginning and ending periods of our sample: 1968 and 1973, and 2004 and 2005, respectively. Table 7 shows the distribution of couples by education level. The table shows that in the earlier period, 19.6 percent of couples were both high school dropouts, 23.4 were both high school graduates, and 6.8 percent were both college graduates. The table shows dramatic increases in both husbands' and wives' education levels from the earlier to the later period, with 23.6 percent of couples both having a college degree in 2004 and 2005. We next examine whether positive assortative mating increased over time. To measure this, we first construct matrices of population shares in which the rows are the husbands' education levels and the columns are the wives' education levels. We then divide the sum of the diagonal cells by the sum of the off-diagonal cells.[9] In the pooled 1968 and 1973 data, this ratio is 1.17. By 2004 and 2005, this ratio increased to 1.31, suggesting that positive assortative mating on education did increase over this period.

Together, these observations suggest the distribution of education types changed significantly from 1968/1973 to 2004/2005, as couples' became more educated overall and more educated people became more likely to mate with one another. Now the question is, how much of the emerging positive correlation in couples' employment changes can be explained by this distributional change? To answer this, we conduct a shift-share analysis in which we hold constant the estimated, education-specific transition matrices, but allow the population weights to vary, over time. In other words, we decompose the effect of changes in the equilibrium probabilities arising from estimates of the transition matrices and the effect of changes in population weights. To do this, we predict employment levels using the equilibrium probabilities for 1968, π_g^{1968}, using population weights from 2005, ω_g^{2005}, and vice versa:

$$\pi' = \sum_g \omega^{2005}{}_g \pi_g^{1968} \text{ and } \pi'' = \sum_g \omega^{1968}{}_g \pi_g^{2005}$$

[9] This method is used in Pencavel (1998).

We report these counter-factual estimates in Table 8. The first two rows of Table 8 duplicate the rows already shown in Table 6. The third row shows the employment-population ratios predicted using the 1968-weighted estimates of π_g and 2005 population weights. The fourth row shows the employment-population ratios predicted using the 2005-weighted estimates of π_g and 1968 population weights. We focus on the steady-state levels of employment-population in a continued expansion (column 1).

In contrast to using the 1968 population weights (first row), using the 2005 population weights (third row) reduces the negative co-movement of couples' employment substantially. For example, the employment-population ratio is 78.4 under independence and is 78.2 when we use the joint matrix, implying only slight negative co-movement within couples. This suggests that shifts in the composition of couple types, and particularly increased assortative mating based on education, matters. We reach a different conclusion, however, when we use the 2005-weighted estimates of π_g and vary the population weights. When we compare the second row (which uses the 1968 population weights) to the fourth row (which uses the 2005 population weights), we do not observe much difference. In both rows, the predicted employment levels using the joint matrix are substantially higher than those predicted using the independent matrix.

How do we reconcile these results? In 1968, there were significant differences in couples' employment correlation across couple types, with employment of couples who were more educated and positively matched on education exhibiting greater positive co-movement. As more couples became educated over time and as positive assortative matching on education increased, this shift in composition alone should have lead to greater observed positive co-movement; however, that is not all what happened. Positive co-movement increased even more among couples types that traditionally exhibited less employment correlation, such that by 2005, there was not much difference in estimates of π_g across couple types. Shifts in population weights alone cannot account for much when we use 2005-weighted estimate of couples' transition matrix. We conclude that, while shifts in composition and increased positive assortative mating on education played a role in the change in couples' employment correlation, the bulk of the change was due to within-group changes in the transition matrix from the earlier to later periods. While couples have become more positively sorted on education, we find that this phenomenon is not the major source of the shift in couples' employment correlation over time.

V. Conclusion

Since 1960, married women's labor force participation rate has doubled from 30 percent to over 60 percent. In addition, their labor force attachment has increased, as evidenced by the rise in average experience level (Blau and Kahn (1997)). The fundamental question we address in this paper is whether these shifts in married women's long-run work behavior impacted couples' abilities to offset each other's labor market shocks. An extensive literature among labor economists examines the "added worker effect," which is defined as the greater propensity of married women to enter the labor force when their husband becomes unemployed. Another strand of the literature has examined the value of "marriage insurance" by emphasizing the negative correlation of couples' income shocks (Kotlikoff and Spivak (1981), Hess (2004), Shore (2007)). In this paper we find that the added worker effect is still important among a subset of couples, but the overall value of "marriage insurance" has diminished due to the greater positive co-movement of employment within couples. While we find that positive assortative matching on education did increase over time, we find that this shift in composition of couple types alone explains little of the increased positive correlation.

Table 1. Classification of (Year t, Year t+1) into Recession/Expansion Categories

Expansion/ Expansion	Expansion/ Recession	Recession/ Recession	Recession/ Expansion
1968-69	1969-70	1970-71	1971-72
1972-73	1974-75	1975-76	1976-77
1973-74	1979-80	1982-83	1980-81
1977-78	1981-82	1991-92	1983-84
1978-79	1990-91	2002-03	1992-93
1984-85	2001-02		2003-04
1985-86			
1986-87			
1987-88			
1988-89			
1989-90			
1993-94			
1994-95			
1995-96			
1996-97			
1997-98			
1998-99			
1999-00			
2000-01			
2004-05			
2005-06			

Notes: Our classification of the business cycle phase follows the NBER classification but in addition allows for laggin behavior of the labor market by dating the end of a recession when the unemployment rate stops increasing.

Table 2a. Labor Market Transitions - Husbands

A. Expansion/Expansion

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	96.8	1.7	1.5
Unemployed t	64.5	24.2	11.3
OLF t	21.3	4.8	73.9

B. Expansion/Recession

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	95.7	3.0	1.4
Unemployed t	59.0	30.9	10.1
OLF t	20.1	4.6	75.3

C. Recession/Recession

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	95.4	3.1	1.4
Unemployed t	57.8	32.8	9.4
OLF t	18.4	6.1	75.5

C. Recession/Expansion

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	95.8	2.7	1.5
Unemployed t	63.9	28.2	7.9
OLF t	21.2	5.6	73.2

Source: March Current Population Surveys. The sample consists of 224,359 couples where the husband is 22-54 years old and are matched across adjacent years. See table 1 for categorization of years into expansions and recessions.

Table 2b. Labor Market Transitions - Wives

A. Expansion/Expansion

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	90.8	1.5	7.8
Unemployed t	55.3	14.2	30.5
OLF t	17.9	2.0	80.1

B. Expansion/Recession

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	87.5	2.4	10.1
Unemployed t	49.2	16.8	34.0
OLF t	15.6	2.2	82.2

C. Recession/Recession

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	88.8	2.4	8.8
Unemployed t	51.5	18.2	30.3
OLF t	14.5	2.0	83.5

D. Recession/Expansion

	Employed t+1	Unemployed t+1	OLF t+1
Employed t	89.5	2.1	8.4
Unemployed t	43.7	17.9	38.5
OLF t	16.3	2.5	81.3

Source: March Current Population Surveys. The sample consists of 224,359 couples where the husband is 22-54 years old and are matched across adjacent years. See table 1 for categorization of years into expansions and recessions.

Table 3. Wife's Entry into Labor Force by Husband's Employment Transition

A. Expansion/Expansion

	O^f_t, E^f_{t+1}	O^f_t, U^f_{t+1}	O^f_t, O^f_{t+1}		Difference in Entry
E^m_t, E^m_{t+1}	18.2	1.8	80.1	100.0	
E^m_t, N^m_{t+1}	21.6	4.2	74.2	100.0	5.8

B. Expansion/Recession

	O^f_t, E^f_{t+1}	O^f_t, U^f_{t+1}	O^f_t, O^f_{t+1}		Difference in Entry
E^m_t, E^m_{t+1}	15.7	1.9	82.5	100.0	
E^m_t, N^m_{t+1}	20.3	6.7	73.0	100.0	9.4

C. Recession/Recession

	O^f_t, E^f_{t+1}	O^f_t, U^f_{t+1}	O^f_t, O^f_{t+1}		Difference in Entry
E^m_t, E^m_{t+1}	14.6	1.9	83.5	100.0	
E^m_t, N^m_{t+1}	15.7	3.9	80.4	100.0	3.1

D. Recession/Expansion

	O^f_t, E^f_{t+1}	O^f_t, U^f_{t+1}	O^f_t, O^f_{t+1}		Difference in Entry
E^m_t, E^m_{t+1}	16.7	2.3	81.0	100.0	
E^m_t, N^m_{t+1}	18.3	3.3	78.4	100.0	2.6

Source: March Current Population Surveys. Calculations are for couples where the husband is employed and the wife is out of the labor force in year t. The number of couples who fall into this category over all all years is 69,608. The numbers refer to the wife's transition probabilities into 3 states, E, U, O in year t+1 by the employment-nonemployment transition of the husband. The last column calculates the difference between entry rates into labor force of wives whose husbands exited employment and entry rates of wives whose husbands remained in employment. See table 1 for categorization of years into recessions and expansions.

Table 4. Probit Estimates of Wife's Entry into Labor Force

Sample: Wives Not in the Labor Force in year t, and Husbands Employed in year t

Dependent Variable = $\text{Prob}(L^{f}_{t+1}/O^{f}_{t,}\ E^{m}_{t})$

	All Years		1968 & 1973 Pooled		2004 & 2005 Pooled	
Indep. Var.	DF/dx	Std.Err.	DF/dx	Std.Err.	DF/dx	Std.Err.
wife's age	**0.004**	0.001	0.004	0.004	0.010	0.006
wife' age squared	**0.000**	0.000	**0.000**	0.000	**0.000**	0.000
wife high school	**0.028**	0.005	0.017	0.011	-0.004	0.029
wife some college	**0.062**	0.006	**0.042**	0.018	**0.069**	0.034
wife college	**0.066**	0.007	**0.110**	0.026	**0.077**	0.038
husband high school	0.002	0.005	-0.008	0.011	0.031	0.032
husband some college	-0.001	0.006	-0.007	0.013	0.044	0.034
husband college	**-0.035**	0.006	**-0.057**	0.012	-0.038	0.033
birth	**-0.075**	0.005	**-0.078**	0.011	**-0.066**	0.024
number of children<18	**-0.008**	0.001	**-0.006**	0.003	**-0.010**	0.006
husband exit	**0.056**	0.013	0.042	0.032	**0.082**	0.043
husband exit*exp-rec	0.035	0.019	-	-	-	-
husband exit*rec-rec	-0.022	0.020	-	-	-	-
husband exit*rec-exp	-0.016	0.021	-	-	-	-
No. of Observations	69,608		7,287		2,912	
Observed Probability	0.189		0.139		0.199	

Source: March Current Population Surveys. Calculations are for couples where the husband is employed and the wife is out of the labor force in year t. The number of couples who fall into this category over all years is 69,608. The dependent variable is the probability that the wife will be in the labor force in year t+1 conditional on not being in the labor force in year t and the husband employed in year t. State and year fixed effects were also included. Numbers in bold refer to coefficients significant at the 5% level.

Table 5. Distribution of Couples by Husband's and Wife's Labor Market Status

	1968/1973		
	Wife Employed	Wife Unemployed	Wife OLF
Husband Employed	40.8	1.6	53.4
Husband Unemployed	0.8	0.1	0.8
Husband OLF	1.2	0.1	1.3
	2004/2005		
	Wife Employed	Wife Unemployed	Wife OLF
Husband Employed	67.1	2.0	22.4
Husband Unemployed	2.2	0.2	0.7
Husband OLF	3.3	0.1	2.2

Source: March Current Population Surveys. The sample consists of 224,359 couples where the husband is 22-54years old and are matched across adjacent years. The labor market status is derived from the employment status last week.

Table 6 - Predicted Employment-Population Ratios - Under Jointness and Independence

			(1) *Continued Expansion*	(2) *First Year of Recession*	(3) *Second Year of Recession*	(4) *First Year of Expansion*
(1)	***1968 Weighted Estimates***	*Predicted Emp-Pop - Joint*	74.15	73.21	73.10	73.50
			(0.538)	(0.404)	(0.363)	(0.301)
		Predicted Emp-Pop - Independent	75.86	74.51	73.59	74.11
			(1.263)	(0.966)	(0.804)	(0.667)
(2)	***2005 Weighted Estimates***	*Predicted Emp-Pop - Joint*	83.23	81.85	81.44	81.32
			(0.345)	(0.29)	(0.268)	(0.243)
		Predicted Emp-Pop - Independent	81.79	80.28	79.78	79.68
			(0.859)	(0.741)	(0.66)	(0.577)

Table 7. Distribution of Couple Types and Assortative Mating

1968 & 1973

Wife's Schooling	Husband's Schooling <12	=12	13-15	>=16	All
<12	19.6	7.1	1.7	0.4	28.8
=12	11.4	23.4	8.3	5.0	48.1
13-15	1.1	3.2	4.1	4.9	13.3
>=16	0.4	1.1	1.6	6.8	9.9
All	32.5	34.8	15.7	17.1	100.0

2004 & 2005

Wife's Schooling	Husband's Schooling <12	=12	13-15	>=16	All
<12	3.9	2.0	0.7	0.3	6.9
=12	2.7	17.2	7.2	3.4	30.5
13-15	1.0	8.0	12.0	7.2	28.2
>=16	0.4	4.0	6.5	23.6	34.5
All	8.0	31.2	26.4	34.5	100.0

Table 8 - Predicted Employment-Population Ratios Using Different Population Weights

				(1) *Continued Expansion*	(2) *First Year of Recession*	(3) *Second Year of Recession*	(4) *First Year of Expansion*
(1)	***1968 Weighted Estimates***	***1968 Population Weights***	*Predicted Emp-Pop - Joint*	74.15	73.21	73.10	73.50
				(0.538)	(0.404)	(0.363)	(0.301)
			Predicted Emp-Pop - Independent	75.86	74.51	73.59	74.11
				(1.263)	(0.966)	(0.804)	(0.667)
(2)	***2005 Weighted Estimates***	***2005 Population Weights***	*Predicted Emp-Pop - Joint*	83.23	81.85	81.44	81.32
				(0.345)	(0.29)	(0.268)	(0.243)
			Predicted Emp-Pop - Independent	81.79	80.28	79.78	79.68
				(0.859)	(0.741)	(0.66)	(0.577)
(3)	***1968 Weighted Estimates***	***2005 Population Weights***	*Predicted Emp-Pop - Joint*	78.16	77.45	77.50	77.85
				(0.575)	(0.433)	(0.356)	(0.301)
			Predicted Emp-Pop - Independent	78.36	77.80	77.47	77.87
				(1.39)	(1.081)	(0.866)	(0.726)
(4)	***2005 Weighted Estimates***	***1968 Population Weights***	*Predicted Emp-Pop - Joint*	79.08	77.43	77.12	76.82
				(0.522)	(0.421)	(0.391)	(0.335)
			Predicted Emp-Pop - Independent	77.66	76.16	75.72	75.68
				(0.944)	(0.78)	(0.682)	(0.579)

Figure 1A.. Difference in Employment to Population: Expansion-Expansion

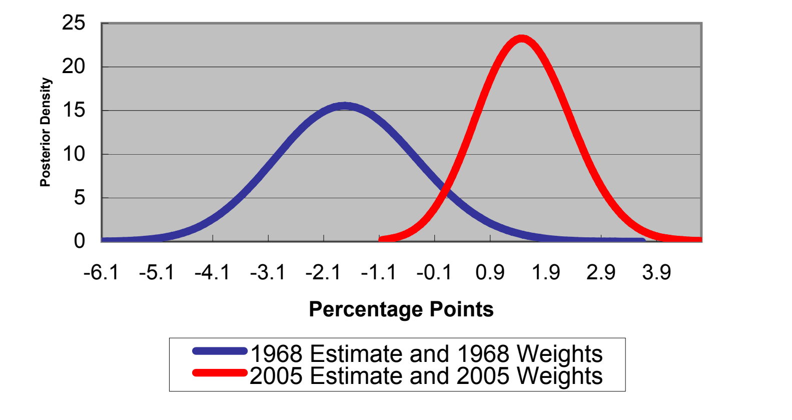


Figure 1C. Difference in Employment to Population: Recession-Recession

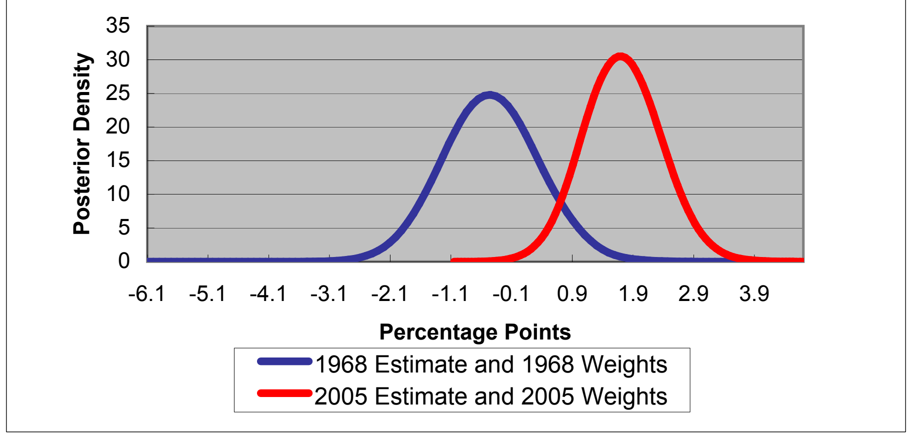


Figure 1B. Difference in Employment to Population: Expansion to Recession

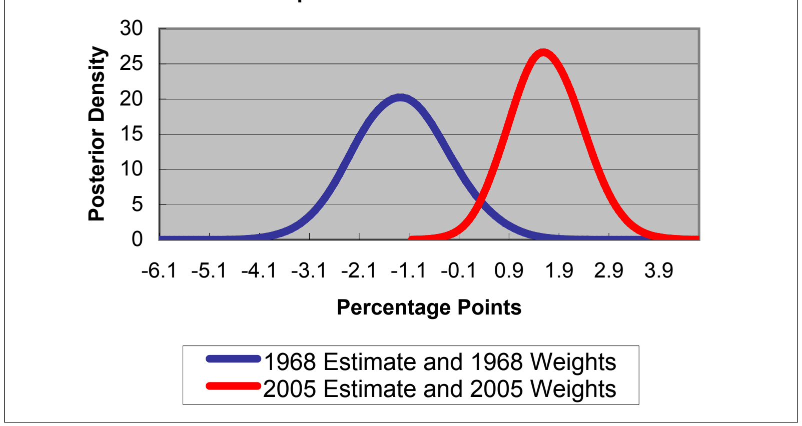
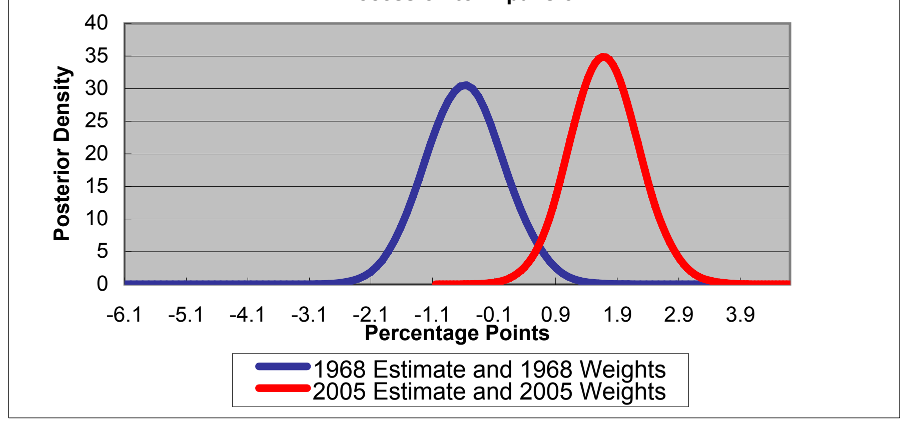


Figure 1D. Difference in Employment to Population: Recession to Expansion



Appendix A: Construction of the Matched CPS Data

The Current Population Survey is constructed such that a housing unit is interviewed for four months (Months in Sample = 1-4), rotates out of the sample for eight months, then returns for another four (Months in Sample = 5-8). For example, a unit that is first interviewed in March (Month in Sample = 1) will be re-interviewed starting in March of the next year (Month in Sample = 5). This allows potentially half of the units interviewed in a given year—those for whom Month in Sample = 1-4—to be matched to their observations in the following year (Month in Sample 5-8). Using unique record numbers available on the CPS data files constructed by Unicon Research Corporation and the above "Month in Sample" variable, one can construct a naïve match across years. In actuality, this method leads to many false matches because the record number is unique to housing unit, not household; if, for example, a family moves out of their house after interviews 1-4 and another family moves in, this method would naively match the two different families. Madrian and Lefgien (1999) discuss the trade-offs inherent in using different sets of demographics to improve the quality of the matches. Following their recommendation, we use gender, race and age to exclude potentially invalid matches. We then use marital status, household identifier, household type and relation of individuals to the household head to match across couples. Our current sample does not attempt to match across potential cohabitants. We include couples in our sample conditional on the husband being between the ages of 22 and 54.

For 1968 to 2005, Appendix Table 1 shows the percentage of these husbands that were matched to a spouse and matched across years. In 1968, for example, the CPS had

27,784 male records in our age range. Of these, 81.1 percent were married with spouse present and matched to valid spouse observations. A well-known fact, which is demonstrated in this table, is that the fraction of men who were married with spouse present fell dramatically over the span of the data, so that only 62.4 percent of male records were matched to spouses in 2005. The third column in the table shows the percentage of couples with Months in Sample = 1-4 who are matched to their observations in the following year. For 1968, 77.7 of the potential couples were matched to observations in 1969. This match rate varies substantially across years and is particularly low during the last four years of our sample, a phenomenon which warrants further investigation.[10] The non-matches are due to migration, mortality, and reporting error.

The clear advantages of the matched March sample are its large size and the number of years it encompasses. As noted above, however, a serious drawback is that it follows housing units, rather than households. Consequently, we must drop households that move due to job change or employment/non-employment transition from our matched samples. Appendix Table 2 compares observed characteristics in year *t* across matched and non-matched households to gauge the bias this may induce. It shows that, on average, non-matched households are 2.9 years younger, slightly less educated and slightly worse-off in terms of labor market variables compared to the matched households. Using the matched samples, then, is likely to bias upwards husbands' and wives' levels of mean employment and participation rates. How this will bias our labor market transitions, however, is less clear (see Peracchi and Welch (1995)).

[10] Another complication is that the Bureau of Labor Statistics scrambled the household identifiers in selected years to preserve confidentiality, which precludes matching across those years.

Appendix B: Description of the Bayesian Econometric Methods

We use a simple Bayesian procedure to estimate the education- and business-cycle-specific transition matrices. Our crucial identification assumption is that, given our segmentation of the data into different business cycle phases and education groups, employment transitions are independent across households. That is, given a business cycle phase and an education group, one household's change in labor market status provides no information about another household.

We assume *a priori* that each row of each transition matrix follows a Dirichlet distribution and that the rows are independent. Further, we assume *a priori* that the transition matrices are independent across business cycle phases and education groups. Updating the posterior is simple in each case given our independence assumptions as we show below.

For illustration purposes, consider the simple case of modeling the husband's transitions between employment and unemployment. In this case, we only have two states, giving us a 2x2 transition matrix. Define p to be the probability that the husband remains employed and q to be the probability that the husband remains unemployed. The prior distribution in this case would be proportional to

$$p^{v_{11}}(1-p)^{v_{12}}q^{v_{22}}(1-q)^{v_{21}},$$

where v_{ij} >0 are the parameters of the Dirichlet distribution. The likelihood would be

$$p^{K_{ee}}(1-p)^{K_{eu}}q^{K_{uu}}(1-q)^{K_{ue}},$$

where K_{ee} is the observed number of employment-to-employment transitions, K_{eu} is the observed number of employment-to-unemployment transitions, K_{uu} is the observed number of unemployment-to-unemployment transitions, and K_{ue} is the observed number of unemployment-to-employment transitions. The posterior distribution is obtained by simply adding exponents and thus is proportional to the updated Dirichlet distribution:

$$p^{K_{ee}+v_{ee}}(1-p)^{K_{eu}+v_{eu}}\,q^{K_{uu}+v_{uu}}(1-q)^{K_{ue}+v_{ue}}.$$

In the case of nine possible transitions the same result applies: add the exponent of the likelihood (i.e. transition counts) to their related exponents in the prior to find the new Dirichlet distribution.

Using a small amount of informative prior information, these Bayesian methods allow us to simulate draws from the posterior distribution that are valid transition matrices (i.e. they have no empty cells) and well-defined equilibrium distributions. In our general case of the joint 9x9 transition matrix estimated for each education pairing and business cycle phase, for each draw from the posterior distribution, we also construct the smaller individual 3x3 transition matrices using standard marginalizing principles. We then use the Kronecker product of these 3x3 matrices as the benchmark of independence. By repeating this exercise 10,000 times, we can provide measures of the uncertainty around objects of interest, such as the employment-population ratio. Further, we can assess the statistical significance of the difference between the joint matrix and the independent benchmark.

The prior we use for the elements of the transition matrix enforces independence and is equivalent to an extra ten observations on each transition for each education pairing and business cycle phase. It was chosen to give reasonable values for average employment-population, labor force participation, and unemployment at the individual level. It is the same for each pairing and business cycle phase; thus, along with the independence assumption, we are placing a substantial prior weight on a neutral view of the joint-ness of labor market activity.

As we are interested in assessing changes in the way couples interact, we use a simple weighting scheme to produce two estimates of transition matrices that are representative of the late 1960s and the mid 2000s. Implicitly, then, we are assuming that the transition matrices are changing across years in our sample. Substantially more complicated methods could be used to estimate this time variation, but we use a simpler approach of discounting observations based on the distance between their years and our year of interest. Thus, for our "1968 estimates", we weight transitions in years closer to 1968 more than those in years closer to 2005 and vice versa for our "2005 estimates."

In terms of the simple example of a husband's transitions above, the two approaches would work as follows, focusing on the employment-to-employment transition in the expansion/expansion phase:

1. 1968-weighted estimate: $\sum_{t=1968}^{2005} \delta^{(t-1968)} 1(t \in E, t+1 \in E) K_{tee} + v_{ee}$

2. 2005-weighted estimate: $\sum_{t=1968}^{2005} \delta^{(t-2005)} 1(t \in E, t+1 \in E) K_{tee} + v_{ee}$

where $0 \leq \delta \leq 1$ is the year weight.

Appendix Table 1. Match Rates Across Spouses and Across Years

Year	# Male Records	% Matched w/ Spouse	%Matched across Years
1968	27784	81.1	77.7
1969	28441	80.3	73.8
1970	27267	80.1	79.0
1973	26300	78.0	50.8
1974	25878	76.9	78.4
1979	31496	71.5	73.6
1980	37717	69.9	77.4
1981	38151	68.6	68.3
1982	34261	67.6	75.7
1983	34771	66.6	73.9
1984	34819	66.1	71.6
1986	34697	64.3	71.4
1987	34385	64.3	73.5
1988	34644	63.4	69.6
1989	32346	63.4	76.0
1990	35501	62.8	74.6
1991	35618	61.7	73.9
1992	35411	61.2	75.2
1993	35239	61.6	55.9
1994	34016	61.3	55.4
1996	29318	61.0	75.2
1997	29834	60.1	75.4
1998	29798	60.1	74.9
1999	29940	60.0	75.0
2000	30581	59.2	81.7
2001	29472	58.8	75.4
2002	47823	63.4	52.3
2003	47657	62.9	52.6
2004	46376	62.9	46.5
2005	45692	62.4	49.4

Source: March Current Population Surveys. Column (1) shows the number of male records aged 22-54. Column (2) shows the fraction matched to spouses. Column (3) shows the match rate across years for couples that could potentially be matched (Month in Sample 1-4 during the first year).

Appendix Table 2. Comparison of Characteristics across Matched and Non-Matched Couples

	Matched Across Years	Not-Matched Across Years
Age of Husband	39.9	37.0
Years of Schooling of Husband	13.1	12.9
Husband Employed (%)	92.9	89.7
Husband Unemployed	3.2	4.8
Husband OLF	3.9	5.5
Husband Weeks Worked	48.0	46.2
Husband Earnings ($2000)	44776	39328
Age of Wife	37.8	34.9
Years of Schooling of Wife	13.0	12.7
Wife Employed	64.7	61.2
Wife Unemployed	2.5	3.7
Wife OLF	32.8	35.2
Wife Weeks Worked	31.9	30.3
Number of Observations	224359	101511

Source: March Current Population Survey 1968-2006. Column (1) shows average characteristics of the couple in year t matched across year t and t+1. Column (2) shows the average characteristics of couples in year t who could potentially be matched to year t+1 (Month in Sample 1-4) but did not have matching observations in year t+1. The potential reasons for non-match are migration, mortality, and reporting error. See Madrian and Lefgren (1999) for further details about non-matches.

Appendix Table 3 - Predicted Unemployment Rate - Under Jointness and Independence

				(1) *Continued Expansion*	(2) *First Year of Recession*	(3) *Second Year of Recession*	(4) *First Year of Expansion*
(1)	***1968 Weighted Estimates***	***1968 Population Weights***	*Predicted Unemployment Rate - Joint*	2.50	3.85	5.44	4.62
				(0.133)	(0.117)	(0.193)	(0.116)
			Predicted Unemployment Rate - Independent	3.14	4.61	6.32	5.48
				(0.319)	(0.291)	(0.348)	(0.227)
(2)	***2005 Weighted Estimates***	***2005 Population Weights***	*Predicted Unemployment Rate - Joint*	2.27	3.09	3.56	3.21
				(0.075)	(0.103)	(0.118)	(0.102)
			Predicted Unemployment Rate - Independent	2.90	3.68	4.31	3.86
				(0.202)	(0.255)	(0.285)	(0.227)

Appendix Table 4 - Predicted Labor Force Participation Rate - Under Jointness and Independence

				(1) *Continued Expansion*	(2) *First Year of Recession*	(3) *Second Year of Recession*	(4) *First Year of Expansion*
(1)	***1968 Weighted Estimates***	***1968 Population Weights***	*Predicted LFP Rate - Joint*	76.03	76.11	77.24	76.96
				(0.535)	(0.405)	(0.345)	(0.285)
			Predicted LFP Rate - Independent	78.30	78.08	78.50	78.17
				(1.241)	(0.958)	(0.779)	(0.651)
(2)	***2005 Weighted Estimates***	***2005 Population Weights***	*Predicted LFP Rate - Joint*	85.13	84.42	84.40	83.97
				(0.336)	(0.279)	(0.252)	(0.232)
			Predicted LFP Rate - Independent	84.19	83.29	83.32	82.83
				(0.833)	(0.714)	(0.616)	(0.554)

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