Trends in Earnings Instability of Couples: How Important is Marital Sorting?[1]

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Abstract: Using the matched March Current Population Surveys for 1968-2008 and 1978-2006 Social Security earnings data matched to several Survey of Income and Program Participation panels, this paper examines the evolution of variability in year-to-year changes in individual and couples' earnings. We find couples' earnings instability remained stable over time due to offsetting trends in men's and women's earnings instability. While men's earnings instability increased, particularly during the 1970s, women's earnings instability declined dramatically. We find some evidence that the correlation of spouses' earnings changes became more positively related over time, but we generally find these correlations to be small. Comparing actual couples to simulated couples who are randomly matched, we find similar trends in earnings instability, suggesting that marital coordination of work and marital sorting are relatively unimportant for instability measures.

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I. Introduction

The U.S. labor market experienced a tremendous rise in earnings inequality across individuals and households over the past four decades. Accompanying this rising earnings gap *between* individuals and households, within-person and within-household variability of earnings also increased. Gottschalk and Moffitt (1994) first documented the rise in this latter component, referred to in the literature as "earnings instability." Other papers using alternative datasets and methods confirmed Gottschalk and Moffitt's basic findings: earnings instability increased dramatically during the 1970s and reached a peak during the 1982 recession but since that period stabilized to the level observed prior to 1982 (see, for example, Cameron and Tracy (1998) and Haider (2001)).

Recently, a number of papers have reported resurgence of earnings instability in the 2000s although the matter is far from settled. Dynan, Elmendorf, and Sichel (2008), Shin and Solon (2008) and Hacker (2006) all report a new rising trend in individual earnings instability in this decade. Hacker (2006) and Dynan, et.al (2008) find a rise in household income volatility as well. The one caveat to these findings is that they all rely on a single data source, the Panel Study of Income Dynamics (PSID). Celik, Juhn, McCue, and Thompson (2009) use a variety of surveys—matched Current Population Survey (CPS), the Survey of Income and Program Participation (SIPP), and the recently available Longitudinal Employment and Household Dynamics (LEHD)—and find little evidence of a recent increase. The Congressional Budget Office study which utilizes Social Security earnings data also document that earnings instability has been steady in the recent period (Dahl, DeLeire, and Schwabish (2007)).

While some of the afore-mentioned studies (Hacker (2006), Dynan et. al (2009) and Dahl, DeLeire, and Schwabish (2008)) have examined variability of household incomes, none have focused on the co-movement of spousal earnings explicitly. In this paper we examine earnings instability of couples, paying particular attention to the correlation of earnings changes for spouses. Earnings of spouses may co-vary due to coordinated labor supply decisions within the household. For example, a large literature examines the "added worker effect," a phenomenon whereby wives increase labor supply to compensate for husbands' job loss (Lundberg (1985) and Stephens (2002)). Spouses may also specialize in the market or the home when young children are present, reflecting the fact that time at home for husband and wife are likely to be substitutes at this stage of the lifecycle (Lundberg (1988)). Both of these phenomena imply a negative correlation between husbands' and wives' earnings changes. On the other hand, there is a well-established pattern of positive assortative mating on education (Mare (1991), Pencavel (1998)). As women become more strongly attached to the labor force, labor market shocks of spouses may become more positively correlated as well. This would suggest that couples earnings should positively co-vary.

In this study we examine the following questions: do spouses' earnings positively co-vary (reflecting assortative matching) or do they negatively co-vary (coordinated labor supply decisions)? Has the correlation changed over time and across successive birth cohorts? Finally, what impact does the correlation of spousal earnings have on the evolution of couples' earnings instability? Our preliminary findings are as follows.

1) While male earnings instability increased, largely over the 1970s, earnings instability among women continuously declined. Due to these offsetting trends, earnings

instability of couples remained remarkably stable during the period, essentially returning to the level of the late 1960s. Based on estimates from Social Security earnings data for the period 1978-2006 matched to the SIPP, earnings instability of couples has actually declined close to 20 percent over this period.

2) We generally find low correlations between husbands' and wives' earnings changes, and that the correlation varies considerably from year to year. In the matched CPS data, we find some evidence that these correlations have become more positive in later years and for more recent cohorts, particularly those born in 1965-1974 relative to earlier cohorts. These results are more pronounced when we select our sample to include only working husbands and wives and also delete earnings observations which are outliers.

3) We find that coordination of spouses' labor supply decisions and positive assortative matching play a minimal role in determining overall earnings instability among couples. To gauge the importance of marital sorting and coordination, we compare earnings instability of actual couples to randomly matched couples. We find very similar trends for actual and simulated couples, suggesting that coordinated labor supply responses and effects of matching are relatively unimportant for instability measures.

Section II describes our data sets and the different sample selection statements used. Section III describes the main earnings instability trends of men, women, married men and women, and couples. Section IV separately examines the correlation of spouses' earnings changes. Section V compares the instability measures across actual and simulated couples. Section VI summarizes our findings and describes our plans for future work.

II. Data

Our empirical results center around estimates of the variance of year-to-year changes in earnings. Here we discuss construction of our two data sets. We use the first year of each year-to-year change to date the change in all of our results (e.g. the 2000-2001 change is dated as 2000 in our figures).

A. Matched CPS

We construct year-to-year matched files from public use March CPS files applying the algorithm suggested by Madrian and Lefgren (1999) to files from survey years 1968-2008 (see appendix for details of the matching process). Because the CPS does not follow sample members who move away from the originally sampled address, it is important to note that the matched sample includes only people who did not change address between the two March interviews that provide the information we need. For both sets of CPS results we use a sample of people aged 25-59 in both years who do not have allocated earnings.[1] Because we cannot match across all years, we end up with 32 two-year panels. We focus on wage and salary earnings and ignore self-employment earnings.

[1] Eliminating allocated earnings is critical for the March files. Following Cameron and Tracy (1998), p. A-4 we delete all individuals who did not respond to questions on the March supplement and had imputations on the majority of questions.

To help describe our basic approach, we begin with the following statistical model:

$$(1) \qquad \begin{aligned} y_{it} &= X_{it}\beta_t + \varepsilon_{it} \\ \varepsilon_{it} &= p_t\mu_i + v_{it} \end{aligned}$$

y_{it} denotes log annual earnings and X_{it} denotes observed characteristics such as age and education. Residual earnings, ε_{it}, is assumed to consist of a person-specific fixed-effect, μ_i, and a transitory component, v_{it}, which is assumed to be independent of μ_i. The term p_t represents factor-loading on the person-specific component, such as return to skill, which may vary by year. Assuming that the factor loading on the permanent component is constant across adjacent years and assuming no serial correlation in the transitory component one can estimate the transitory variance of earnings, σ^2_{vt} by taking first difference in the residuals as in the following:

$$(2) \qquad \sigma^2_{vt} + \sigma^2_{vt+1} = E(\varepsilon_{it+1} - \varepsilon_{it})^2 .$$

What we will term our log-difference measure of earnings instability is the closely related standard deviation of the change in log earnings residuals, $\Delta\varepsilon_{it}$. In constructing this measure we essentially follow the methods in Shin and Solon (2008) to provide results that are comparable to their results and to others using similar methods. We run annual regressions of year-to-year changes in the log of wage and salary earnings on a quadratic function in age and calculate the standard deviation of the residuals from this regression as our first measure of earnings instability. In these estimates we also trim outliers and eliminate most top-coded earnings from the sample by deleting the top and bottom 1 percent of non-zero earnings in each year, leaving us with a total of 364,439 observations of individuals and 85,263 observations of couples (see Table 1).

One problem with this approach is that, because we drop those with zero earnings in either year, our measure of earnings instability does not include the effects of non-employment spells that last more than one year. This is particularly problematic where we would like to examine long-term changes in instability for women. As an alternative that more fully captures the effects of non-employment, we construct a second measure of earnings instability based on percent changes using the average of earnings over the 2-year period of the change as base. That is,

$$(3) \qquad \Delta\tilde{y}_{it} = \frac{y_{it} - y_{i,t-1}}{\left(\frac{y_{it} + y_{i,t-1}}{2}\right)}$$

where, as above, y represents annual earnings.[2] Where earnings are zero in both periods, we assign a value of zero to this measure. Following the method we use with log differences, we remove the predictable effects of age on wage growth by regressing these yearly percent changes on a quadratic function in age for each year and refer to the standard deviation of the residuals from this regression as our percent-change measure of earnings instability. Results of the two measures can differ either because the percent-change sample includes zeros and outliers that are excluded in the log-difference measure, or because of the way we measure changes. We have also examined estimates that use the log-difference sample with the percent-change formula, and found that they

[2] This measure has also been used in the instability literature by Dahl, DeLeire, and Schwabish (2008), while Dynan, Elmendorf, and Sichel (2007) similarly use a somewhat different average across years for the base. It is also commonly used in measures of job flows (e.g. Davis, Haltiwanger, and Schuh, 1996). Using average earnings as the base rather than t-1 earnings has the advantage of being defined when earnings are zero in t-1, and of limiting extreme values generated by very low earnings in t-1. It is simple to show that the percent change in earnings measured in this way cannot fall outside the range –2 to 2.

tracked the log-difference measures quite closely. Because they provided little additional information we do not present them here, but it is worth noting that where the log and percent estimates differ it is primarily due to the difference in samples. Our sample of individuals for this measure is 515,457 observations and the married sample is approximately twice as large when we include the zeros with 173,339 couple observations.

B. SIPP-SSA matched data

Our second set of results is based on a confidential data set that combines administrative earnings records with Survey of Income and Program Participation (SIPP) survey data. Our sample of individuals is drawn from respondents to the 1990-1993, 1996, 2001, and 2004 SIPP panels who provided the information needed to validate matches to Social Security Administration (SSA) earnings records. Individuals had to be at least 15 years old at the time of their second SIPP interview to be eligible for inclusion in the matched data. For matched individuals, we have annual earnings for 1978-2006 based on annual summaries of earnings on jobs recorded in SSA's Master Earnings File. The primary source of the earnings information is W-2 records, but self-employment earnings are also included. We include employees' contributions to deferred compensation plans as part of our earnings measure. We obtain marital histories, educational attainment, and women's fertility histories from the SIPP. Age and gender are based on combined information from the SIPP and SSA sources.

As we did with the CPS, we restrict our sample in each year to individuals aged 25-59. While detailed survey information on employment and earnings are collected for each individual only over the relatively short window of their SIPP panel, from the administrative records we have earnings for each year between 1978 and 2006. Our analysis includes all matched SIPP respondents in any years in which they meet the 25-59 age restriction. Thus for a 50 year old interviewed in the 1990 SIPP panel, we use earnings for 1978-1999, while for a 20 year old in 1990 we use earnings for 1995-2006. As Table 1 illustrates, in total we have about 5 million person/year observations, or roughly 170,000 people per year.

Where we condition on marital status, we can only use earnings for years in which we can determine whether or not someone is married. To determine marital status, we use the marital history information collected in the relevant SIPP panel with some additional updates from changes in later waves of that panel. This largely gives us the information we need for years leading up to or during the SIPP panel, but not for the years after the panel is over. Thus when we condition on marital status we have much smaller samples at the end of our period than at the beginning because in later years we can only use the most recent panel(s). For example, in 2004-2006 we can only identify married men and women if they are members of the 2004 SIPP panel, while in 1978 we can in principal use data on any matched person born between 1919 and 1953 from any of the SIPP panels as long as they provided a marital history.

One further complication in examining the earnings of married couples is that we only have earnings for both members of couples identified in the second wave of their SIPP panel. For a sample member who divorced before the start of the SIPP panel, we have earnings for that sample member and know in which prior years they were married, but we cannot, for example, look at the combined spousal earnings in those earlier years because their previous spouse is not in the sample.

III. Trends in Earnings Instability of Couples

Before we describe earnings instability of couples, we first examine earnings instability for all men and all women who are 25-59 years old in our datasets. Figure 1 compares earnings instability among all men in the two datasets. The top panel shows instability of earnings measured in percent changes including those with zero earnings while the bottom panel shows instability of log differences which include only those with non-zero earnings. As documented in the literature, earnings instability of men (both including and not including zero earnings) rose during the 1970s and peaked during the 1982 recession. In both datasets, there is cyclical variation in male earnings instability but little trend since the 1982 recession. In contrast to some of the previously cited authors, we find no evidence of an upward trend in the recent period.[3]

The pattern for women is remarkably different. Figure 2 illustrates earnings instability for all women aged 25 to 59. The top panel, which includes zero earnings, shows a decline in instability of approximately 18-20 percent in the SIPP-SSA data since 1978. The CPS time series, which goes back further to the late 1960s, has a less dramatic decline (slightly less than 10 percent). When we focus on non-zero earners only

[3] We find a level difference in earnings instability based on log differences across the two data sets, SIPP-SSA and matched CPS which we are in the process of investigating. The instability measures based on percent changes, however, are remarkably close in terms of both levels and trends.

(illustrated in the bottom panel) we find a much larger decline of 30 percent or more in the CPS data.

As the first panel of Table 2 illustrates, women who are out of the labor force and have successive zero earnings (the first column) have very low instability relative to other women, while those who transition in and out of employment (the second column) have high earnings instability. The entry of women into the labor force during the late 1960s and 1970s would have increased the percent-change measure of instability if it had come about mostly through a shift from continuous non-employment to short spells of employment, but the second panel of Table 2 shows that this was not what happened. The share of women working continuously increased dramatically over this period, with the increase coming from reductions in the shares of both the continuously non-employed and those employed over only part of the two-year window. The countervailing effects of the decrease in continuous non-employment and the increase in continuity among those employed led to a more muted trend in the measure that includes zeros.

Figures 3 and 4 present our instability measures for married men and women. A key question is whether trends in earnings instability differ by marital status. Figures 3 and 4 show that, by and large, trends for married men and women are very similar to the overall trends. Unsurprisingly, earnings instability levels are lower for married men, though the difference is small in the CPS estimates. The only other notable difference is that in the CPS the decline in instability is somewhat larger for married women than women overall, particularly when we exclude zeros and examine variability of log differences. This happens because in the first decade of the CPS period married women have higher than average instability, but by the 1980s this difference has largely disappeared.

In Figure 5 we present estimates of the instability of couples' combined earnings. Couples' earnings have lower levels of instability than the earnings of married men alone (which are in turn more stable than the earnings of women). The CPS estimates indicate that the level of instability for couples' earnings is little changed since the late 1960s, whether one measures instability including those without earnings or excluding them. While the SIPP-SSA estimates suggest that instability has fallen for couples, this impression is largely driven by the fact that the series starts during a period of relatively high instability. Both series show a modest decline since the levels at the peak of the early-1980s recession onwards, but the longer time frame of the CPS suggests that at that point instability was high relative to the level of the 1970s.

IV. Correlation of Spouses' Earnings Changes

The previous section showed that couples' earnings instability remained remarkably stable since the late 1960s due to offsetting trends among men and women. To the extent that household members share resources, these results suggest that consumption and economic well-being may have been less affected than we would have thought given the changes in individual earnings volatility. In this section we examine to what extent the smoothness of volatility trends for couples reflect coordinated labor supply decisions of husbands and wives. For example, wives can offset husbands' job loss by entering the labor force. On the other hand, if men and women tend to be married to spouses with similar labor market characteristics, correlated labor market shocks due to such positive assortative matching may work against achieving stability of household earnings.

To motivate our basic approach, we expand our statistical model of earnings to apply to couple *i*:

$$
(4)\qquad
\begin{aligned}
y_{it}^{M} &= X_{it}^{M}\beta_t + \varepsilon_{it}^{M}\\
\varepsilon_{it}^{M} &= p_t\mu_i^{M} + \nu_{it}^{M}\\[1ex]
y_{it}^{F} &= X_{it}^{F}\beta_t + \varepsilon_{it}^{F}\\
\varepsilon_{it}^{F} &= p_t\mu_i^{F} + \nu_{it}^{F}
\end{aligned}
$$

where the superscripts *M* and *F* refer to the husband and the wife respectively. ρ_{vt} is the correlation of transitory shocks, $\rho_{vt} = corr(\nu_{it}^{M}, \nu_{it}^{F})$ which will include the effects of assortative matching, local labor market conditions and other family-specific shocks. With the simplifying assumptions that there is no serial correlation in transitory shocks and that factor loadings are constant across the two years, correlation of changes in husband's earnings and changes in wife's earnings will give us an estimate of the correlation of transitory shocks.

However, the simple set-up above does not distinguish between wages and labor supply decisions. The raw correlation of couples' earnings changes, call it ψ_{vt}, will include not only any underlying correlation in transitory shocks ρ_{vt} but also coordinated changes in labor supply. One strategy for gauging the importance of matching and joint labor supply decisions is to build a counterfactual correlation, ψ_{vt}^{1}, by drawing random matches of married men and married women's earnings innovations within state and year. To the extent that the correlation observed among the randomly rematched couples differs from the correlation observed among actual couples, this would point to an important role for both matching and for joint labor supply decisions. To further isolate the effect of joint labor supply decisions from marital sorting, we also build a second counterfactual correlation, ψ_{vt}^{2}, by grouping couples based on observable characteristics such as education of the husband and wife and age of husband and wife in addition to state and year, and randomly matching couples within groups.[4] The difference between the actual and this second counterfactual correlation, $\psi_{it} - \psi_{it}^{2}$, isolates the role of coordinated labor supply responses.[5]

Figure 6 plots the correlation of couples' earnings changes using the CPS data. The correlations are generally small in size ranging from -.02 to .06 but the estimates are noisy from year to year. To try to identify patterns of change over time we calculate a smoothed version of the correlations by essentially taking a weighted average over several years of surrounding estimates to come up with a predicted correlation for each year.[6] The top panel reports the correlations based on percent changes (which include zeros) and the bottom panel reports the correlations based on log differences. The smoothed series indicate an increase in the correlation of couples' earnings changes from zero to a small positive value. As shown in the bottom panel, the pattern is somewhat

[4] More precisely, we define 13 education classifications for the couple based on cross-classification of five education classes for each spouse: less than high school, high school graduate, some college, college graduate, more than college. We define 3 age groups, 25-34, 35-44, 45-59, thereby allowing for 9 possible couple types based on age. Overall, this results in 117 (13x9) groups by year and state in the CPS. With the SIPP-SSA data, we do not have current state of residence except during a sample couple's SIPP panel, so we are limited to using age, education, and year to do the rematching.

[5] The assumption here is that observable characteristics such as education and age sufficiently control for matching. Of course it is possible that husbands and wives match on characteristics we do not observe in the data or that our state controls may not adequately control for local labor market conditions. In these cases, matching and local labor market conditions will be confounded with joint labor supply decisions.

[6] More precisely, we use a version of locally weighted scatter-plot smoothing (LOWESS) which applies weighted linear regression to a localized subset of the data around each data point to produce a predicted value of that data point. We set the bandwidth for these estimates so that the smoothed correlations are based on the correlations from the 3 preceding and 3 following years.

more pronounced when we exclude zero earnings and focus on earnings changes among those who are working in adjacent years.

In Figure 7 we plot the smoothed correlations based on our sample of married couples as well as the two simulated correlations based on random rematching of husbands and wives from our sample of couples. The top panel again relays the results using the percent changes and including zero earnings while the bottom panel focuses on log differences, excluding non-workers. As the top panel illustrates, earnings correlations of randomly matched couples (matched within the same year and, for the CPS, the same state) decrease slightly over time from a small positive number to a small negative number. The correlations of husbands and wives who are randomly rematched within age and education cells also show a rising trend although it is not as pronounced as the trend in the correlations observed among actual couples.

Comparison of the actual and simulated correlations suggests that positive assortative matching and changes in the way in which couples coordinate labor supply both contributed to increasing correlation of couples' earnings changes. The labor supply responses, however, suggests that time at home for husbands' and wives' are complements and that the complementarity has become stronger. Of course it may also be the case that husbands and wives are similar in unobservable ways (which we do not take account of here) and this has lead to a greater positive correlation in transitory shocks.

To further explore the determinants of correlations of husbands' and wives' earnings changes, we also apply the following regression framework to the CPS data. We compute for each couple *i* the product of earnings changes in year *t*, $\Delta\varepsilon_{it}^{M} \cdot \Delta\varepsilon_{it}^{F}$, which is the couple's contribution to the cross sectional covariance. We scale the variable by the appropriate standard deviations of male and female residuals. Our dependent variable is defined as the following:

$$(5) \qquad \pi_{it} = \frac{\Delta\varepsilon_{it}^{M} \cdot \Delta\varepsilon_{it}^{F}}{\sigma_{t}^{M} \cdot \sigma_{t}^{F}}.$$

We run the following regression using π_{it} as the dependent variable and wife's cohort dummies, wife's age dummies and the presence of children as independent variables as in the following:

$$(6) \qquad \pi_{it} = \beta Cohort\_Dum_{it} + \gamma Age\_Dum_{it} + \delta Kids_{it} + u_{it} \quad .$$

We define five different birth cohort dummies starting with the 1925-34 cohort and ending with the 1965-74 cohort. Our age categories are 25-34, 35-44, and 45-59 years old. We control for the number of children in the household under the age of 6.

We report our regression results in Tables 3 and 4. Table 3 reports results based on percent changes including zero earnings. The first column reports results using only cohort dummies with the omitted group being women born in 1925-34; column (2) adds age dummies, column (3) adds number of children under age 6 and the last column also controls for education levels of spouses. While the age and number of children are significant, cohort dummies are positive but insignificant. Table 4 reports results for log differences among those with positive earnings. The cohort dummies are now more positive and often significant suggesting that couples' correlation of earnings is more positively related for cohorts born in later years. One caveat to these regressions is the low R-squares reported in the last row. While some of our explanatory variables are significant and there is some weak evidence that couples' earnings positively co-vary for the later birth cohorts, overall our explanatory variables perform poorly in terms of explanatory power.

V. Impact of Coordination and Matching on Earnings Instability of Couples

In this section we examine to what extent correlations in couples' earnings changes have affected the overall trend in earnings instability of couples. Denote the combined earnings of couple *i* as $y_{it} = y_{it}^{M} + y_{it}^{F}$ and using our percent change definition, we have the following relationship:

$$\text{(7)} \qquad \Delta\tilde{y}_{it} = \frac{\left(y_{it} - y_{i,t-1}\right)}{\overline{y}_{it}} = \frac{\Delta y_{it}^{M} + \Delta y_{it}^{F}}{\overline{y}_{it}^{M} + \overline{y}_{it}^{F}} = \overline{s}_{it}^{M}\,\Delta\tilde{y}_{it}^{M} + \overline{s}_{it}^{F}\,\Delta\tilde{y}_{it}^{F}$$

Equation (7) decomposes the change in couples' earnings change into the share weighted sum of individual earnings changes where $\overline{s}_{it}^{M} = \dfrac{\overline{y}_{it}^{M}}{\overline{y}_{it}}$. If the earnings shares in the above equation could be treated as constants, then it would be straightforward to decompose the variance of couples' earnings changes into the contributions of the variance of husbands' earnings changes, variance of wives' earnings changes, and the covariance term. But since changes in spouses' earnings change the shares, the actual decomposition of the above will be much more complicated.

As an alternative, we use our random rematching of couples to build two counterfactual instability measures that should isolate the effects of assortative matching of spouses and coordination of labor supply. As we laid out earlier in describing the correlations in section IV, we randomly rematch couples within state and year (which we term our unconditional rematch) and also randomly rematch couples within year, state, and education and age categories of the couple (conditional rematch). Thus in addition to the actual standard deviation of couples' earnings changes, σ_{yt}, we also build σ_{yt}^{1} which is based on random matching, and σ_{yt}^{2} which is based on rematching within observable groups. In theory, the difference in earnings instability between actual, σ_{yt},and randomly rematched couples, σ_{yt}^{1}, should indicate the importance of marital sorting as well as coordinated labor supply decisions. Comparison of actual couples and couples randomly rematched within group should isolate further the impact of joint labor supply decisions on overall earnings instability trends.

Figures 8 and 9 illustrate our findings. Figure 8 reports the results based on CPS data. The top panel shows the results for percent changes including zeros and the bottom panel shows the results for log differences excluding zeros. The figures show that earnings instability among actual and simulated couples track each other very closely. The similarity of the trends suggests that spouse-specific factors—either matching or coordination of labor supply—have minimal impact on the evolution of earnings instability among couples. This is perhaps not surprising given our earlier results that the correlations were generally small and that observable characteristics such as birth cohort, age, education, or number of children had little explanatory power.

One concern is the small sample sizes of couples in the CPS data. Particularly for randomly rematched couples within group, the probability of rematching with your actual spouse may be non-trivial in some cells. Carrying out the same exercise with the SIPP-SSA data provides a nice check since the sample sizes of couples are nearly 10 times the size of the CPS. Figure 8 shows results for actual couples and couples rematched within group using SIPP-SSA data. As in the CPS results, we find little difference between the actual and simulated couples.

V. Summary and Plans for Future Work

In this paper we examined the correlation of year-to-year innovations in earnings of husbands and wives. We find the correlation of these short-term changes to be generally low. There is some evidence that the correlation has increased over time, similar to earlier findings that weeks and hours of work have become more positively related among spouses (Juhn and Potter (2008)). Using the PSID, Shore (2006) finds a negative correlation of spousal earnings changes of -0.10. The correlations we calculate in the CPS and SIPP-SSA data are positive and much smaller in magnitude with the average across years being roughly .02. The low correlations we document here are also somewhat at odds with the added worker literature (see Stephens (2002) and Devereux (2004) for example) which find negative co-movement of spouses' earnings and labor supply. A major difference is that the nature of the earnings shocks we capture in this paper, year-to year changes, are likely to be short-term and less permanent than those captured in the added worker literature. While the matched CPS is restricted to the two-year panel structure, the SIPP-SSA data encompass a much longer panel data of individuals and couples which will allow us to examine longer run changes in earnings in future work.

We also found that the correlation of spouses' earnings changes mattered little for the evolution of earnings instability of couples. Earnings instability of couples has remained remarkably stable since the late 1960s due to the offsetting trends in male and female earnings instability. While male earnings instability increased slightly and a lot has been written on this particular topic, a more remarkable story is the fall in women's earnings instability. Our results show that the decline in women's instability offset men's increase but exactly who was married to who mattered little. Our focus in this paper has been on earnings instability. In future versions we will also explore the impact of marital sorting and labor supply on inequality of long-term earnings across couples. Over the four past decades women have gained substantially in terms of earnings while male earnings have fallen, particularly for those with little education. The extent to which wives' earnings offset the increase in male inequality would depend on matching and labor supply behavior. Again the long panel available in the SIPP-SSA data would allow us to explore this question.

Appendix A: Construction of the Matched CPS Data

Current Population Survey housing units are interviewed for four months (Months in Sample = 1-4), rotate out of the sample for eight months, then return 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 public-use 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 Lefgren (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. Appendix Table 1 reports the match rates across years. The match rate varies substantially and is particularly low since 2001, the year that the March CPS sample sizes were increased to allow more precise estimates of minority groups for State Child Health Insurance Program (SCHIP). These years therefore contain households which cannot be feasibly matched across years.

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 lose 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 men to gauge the bias this may induce. The top panel shows the average difference across all years, 1968-2006. It shows that, on average, non-matched men are younger and worse in terms of labor market variables. Using the matched samples, then, is likely to bias upwards levels of mean earnings and employment rates. How this will bias earnings instability, however, is less clear (see Peracchi and Welch (1995)). Since our paper focuses on trends, it would be problematic if the bias varied across years. We investigate this in the next two panels. We compare two peak years of the business cycle, 1968-69 and 1999-2000. We choose 1999-2000 mainly due to the fact that it is the last business cycle peak before the introduction of the SCHIP sample expansion which is likely to distort our comparison. We find that the bias has decreased over time in terms of employment and increased in terms of earnings. Overall, we find little systematic evidence of increasing bias over time.

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Table 1: Sample sizes

CPS estimates	Person/years		Average per year	
	All changes	Log differences	All changes	Log differences
Men	251,299	195,057	7,853	6,096
Women	294,484	169,382	9,203	5,293
Married men	189,837	152,106	5,932	4,753
Married women	207,463	112,325	6,483	3,510
Couples	173,339	85,263	5,417	2,664

SIPP-SSA estimates	Person/years		Average per year	
	All changes	Log differences	All changes	Log differences
Men	2,414,856	2,035,506	86,245	72,697
Women	2,566,092	1,841,473	91,646	65,767
Married men	810,306	721,491	28,940	25,768
Married women	920,772	625,422	32,885	22,337
Couples	765,102	474,028	27,325	16,930

Table 2: Women's Employment Status and Earnings Instability (Percent changes)

Year	Earnings Instabilitity		
	Nonemployed Both Years	Partly Employed	Full-year Employed Both Years
1967-69	0.029	1.266	0.371
1978-80	0.042	1.262	0.409
1988-90	0.034	1.237	0.431
1998-00	0.024	1.253	0.422
2004-06	0.013	1.272	0.439

Year	Employment Status		
	Nonemployed Both Years	Partly Employed	Full-year Employed Both Years
1967-69	0.378	0.343	0.279
1978-80	0.295	0.356	0.349
1988-90	0.210	0.319	0.471
1998-00	0.210	0.273	0.517
2004-06	0.239	0.241	0.520

Source: March Current Population Surveys. Column (1) includes women who were not employed in both years. Column (2) includes women who transitioned in and out of employment as well as women who were part-year employed both years. Column (3) refers to women who were employed full-year (at least 48 weeks) in both years. Bottom panel reports the standard deviation of year-to-year earnings changes by group. Earnings instability is non-zero even for those non-employed in both years due to the fact that we regress earnings changes on a quadratic in age in the first stage and take standard deviation of the residuals.

Table 3. Correlation of Spouses' Percent Earnings Changes - Includes Zero Earnings

	Dep Var = Product of earnings changes for husband and wife							
	(1)		(2)		(3)		(4)	
Intercept	0.022	**	-0.010		0.008		0.035	**
	(0.008)		(0.011)		(0.011)		(0.014)	
Wife Born 1925-34	---		---		---		---	
Wife Born 1935-44	-0.008		0.004		0.004		0.008	
	(0.011)		(0.010)		(0.010)		(0.011)	
Wife Born 1945-54	-0.008		0.004		0.003		0.002	
	(0.010)		(0.010)		(0.010)		(0.010)	
Wife Born 1955-64	-0.007		0.016		0.016		0.011	
	(0.010)		(0.011)		(0.011)		(0.011)	
Wife Born 1965-74	0.005		0.016		0.018		0.030	**
	(0.012)		(0.013)		(0.013)		(0.014)	
Wife 25-34			---		---		---	
Wife 35-44			0.026	**	0.015	**	0.016	**
			(0.007)		(0.008)		(0.008)	
Wife 45-59			0.035	**	0.018	**	0.018	**
			(0.008)		(0.009)		(0.009)	
# Children <6					-0.020	**	-0.018	**
					(0.005)		(0.005)	
Education Controls	**No**		**No**		**No**		**Yes**	
Sample size	161020		161020		161020		161020	
R-squared	0.0000		0.0001		0.0002		0.0002	

Notes: Data from 1968-2009 March Current Population Surveys. The sample includes couples where the husband and wife are both 25-59 years old, where the wife is born between the years 1925 and 1974. Dependent variable is the product of earnings changes for husband and wife, where the earnings changes are first regressed on a cubic function in age. Each couple is weighted by the person weight of the husband. "Education Controls" refer to dummies for couple type based on four education categories of the husband and four education categories of the wife.

Table 4. Correlation of Spouses' Log Earnings Differences - Excludes Zero Earnings

	Dep Var = Product of earnings changes for husband and wife							
	(1)		(2)		(3)		(4)	
Intercept	0.008		-0.035	**	-0.040	**	-0.031	
	(0.015)		(0.018)		(0.018)		(0.025)	
Wife Born 1925-34	---		---		---		---	
Wife Born 1935-44	-0.001		0.006		0.006		0.012	
	(0.018)		(0.018)		(0.018)		(0.018)	
Wife Born 1945-54	0.009		0.021		0.021		0.031	
	(0.017)		(0.017)		(0.017)		(0.018)	
Wife Born 1955-64	0.021		0.044	**	0.044		0.053	**
	(0.017)		(0.017)		(0.017)		(0.019)	
Wife Born 1965-74	0.054	**	0.073	**	0.072		0.099	**
	(0.019)		(0.020)		(0.020)		(0.022)	
Wife 25-34			---		---		---	
Wife 35-44			0.041	**	0.043	**	0.050	**
			(0.011)		(0.011)		(0.011)	
Wife 45-59			0.046	**	0.050	**	0.060	**
			(0.012)		(0.013)		(0.014)	
# Children <6					0.007		0.009	
					(0.008)		(0.008)	
Education Controls	**No**		**No**		**No**		**Yes**	
Sample size	80320		80320		80320		80320	
R-squared	0.0002		0.0003		0.0004		0.0005	

Notes: Data from 1968-2009 March Current Population Surveys. The sample includes couples where the husband and wife are both 25-59 years old, where the wife is born between the years 1925 and 1974. Dependent variable is the product of earnings changes for husband and wife and where change in log earnings are first regressed on a cubic function in age. Those with zero earnings and outliers below 1st percentile and above 99th percentile are deleted from the sample. Each couple is weighted by the person weight of the husband. "Education Controls" refer to dummies for couple type based on five education categories of the husband and five education categories of the wife.

Appendix Table 1. Match Rates Across Years

Year	# Male Records	# Male Records in Month-in-Sample 1-4	%Matched across Years
1968	28130	14087	75.2
1969	28509	14437	72.1
1970	27160	13659	76.5
1973	25775	12949	49.5
1974	25276	12315	74.9
1979	30516	15379	70.7
1980	36418	18322	73.2
1981	36842	18179	65.4
1982	33323	16759	72.3
1983	33887	17055	70.0
1984	33718	16833	68.1
1986	33747	16850	66.7
1987	33411	16809	69.2
1988	33882	17116	64.4
1989	31626	15835	70.3
1990	34700	17518	69.2
1991	35028	17370	68.9
1992	34638	17228	69.5
1993	34482	17241	52.1
1994	33328	15413	51.2
1996	29089	14588	70.2
1997	29662	15038	70.0
1998	29766	15043	70.6
1999	30046	15144	70.2
2000	30607	13813	76.1
2001	49367	24568	50.9
2002	48790	24426	52.0
2003	48711	24539	52.5
2004	47808	23542	46.5
2005	46981	23372	49.1
2006	46569	23433	49.6
2007	45229	23318	50.7

Source: March Current Population Surveys. Column (1) shows the number of male records aged 25-59 in both years. Column (2) shows the number men who are in Months-in-Sample 1-4 and could potentially matched. Column shows the match rate among Months-in-Sample 1-4 who could potentially matched.

Appendix Table 2. Comparison of Matched and Non-Matched Men 25-59

	Matched	Not-Matched	Difference
A. All Years			
Age	3.341.2	37.9	
Years of Schooling	13.0	12.8	0.2
% Employed	88.0	80.9	7.1
% Unemployed	4.1	6.0	-1.9
% OLF	7.9	9.7	-1.8
Average Weeks Worked	45.5	42.6	2.9
Average Earnings (2000 Dollars)	35,824	31,376	4,448
Number of Observations	353,152	208,932	144,220
B. 1968			
Age	42.0	38.3	3.7
Years of Schooling	11.4	11.5	-0.1
% Employed	94.5	84.6	9.9
% Unemployed	1.7	3.1	-1.4
% OLF	3.8	5.2	-1.4
Average Weeks Worked	48.4	42.7	5.7
Average Earnings (2000 Dollars)	29,151	25,704	3,447
Number of Observations	10,593	3,486	7,107
C. 1999			
Age	41.5	37.5	4.0
Years of Schooling	13.5	12.8	0.7
% Employed	87.6	81.3	6.3
% Unemployed	2.9	4.6	-1.7
% OLF	9.4	11.0	-1.6
Average Weeks Worked	45.4	43.7	1.7
Average Earnings (2000 Dollars)	38,988	32,045	6,943
Number of Observations	10,635	4,507	6,128

Source: March Current Population Survey 1968-2008. Column (1) shows average characteristics of men in year t matched across year t and t+1. Column (2) shows the average characteristics of men 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). The bottom two panels compare matches and non-matches in 1968 (the first available survey year) and 1999 (last business cycle peak year before the oversampling for SCHIP starting in 2001).

Fig. 1a: Instability estimates, percent differences, all men

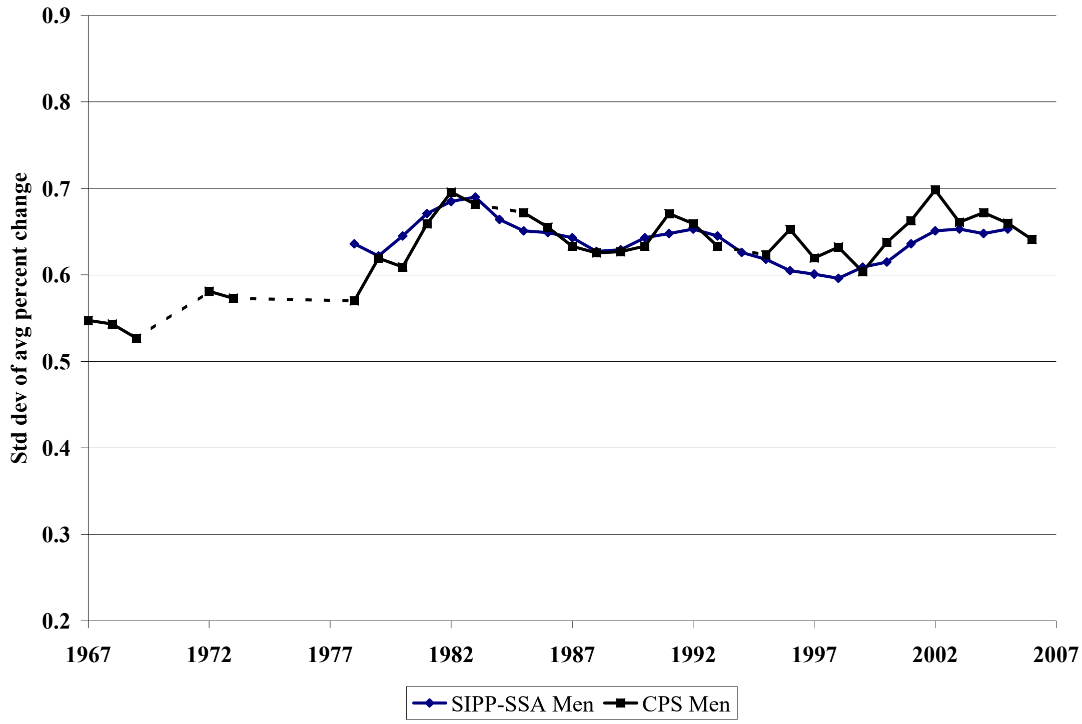

Fig. 1b: Instability estimates, log differences, all men

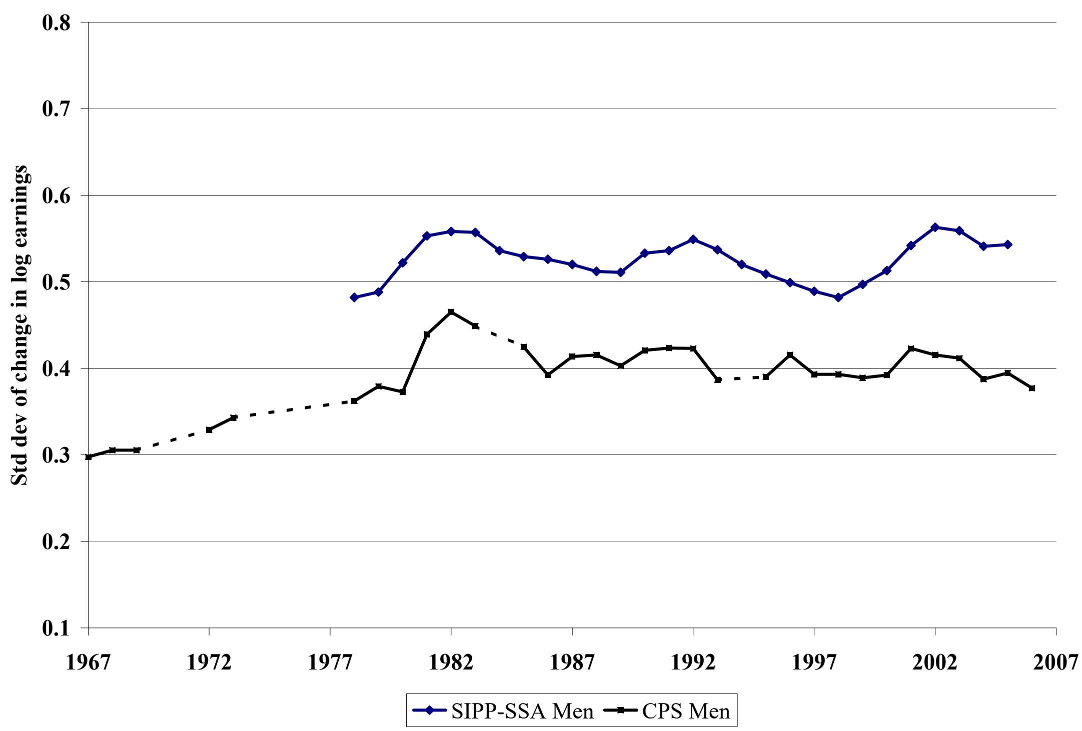

Fig. 2a: Instability estimates, percent differences, all women

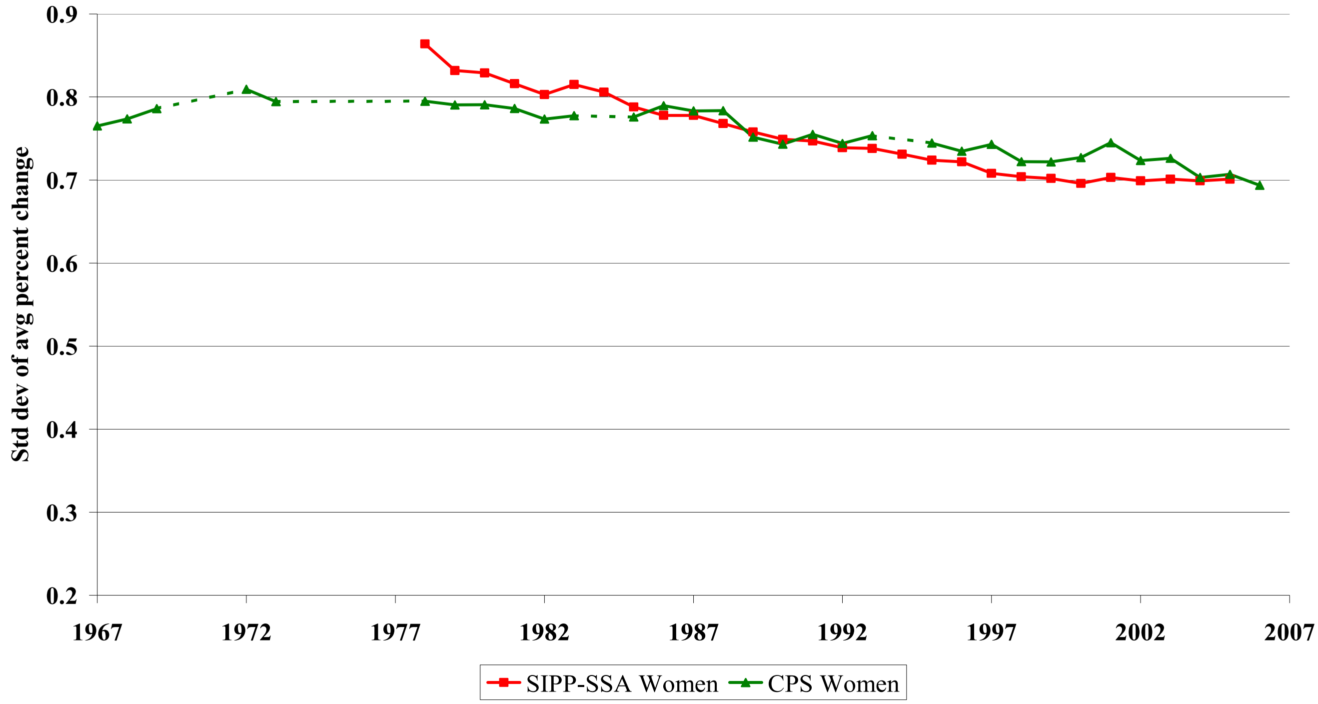

Fig. 2b: Instability estimates, log differences, all women

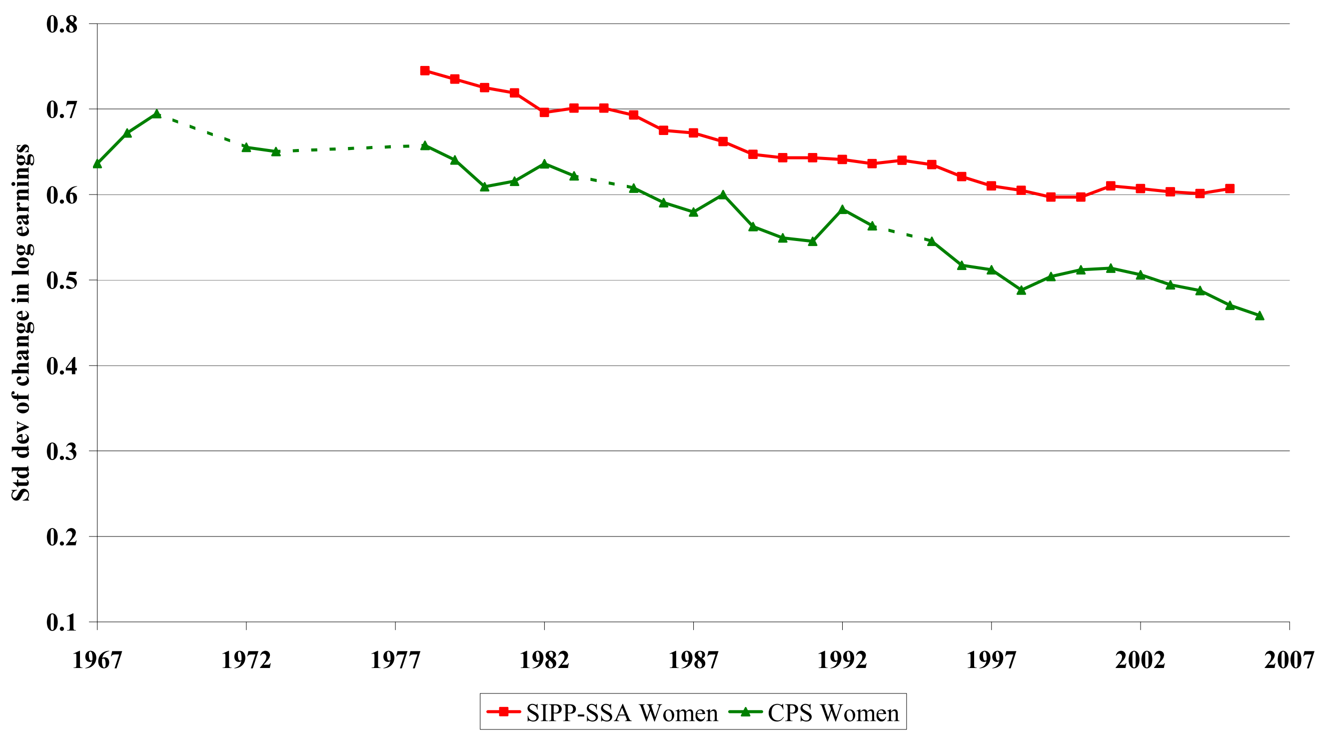

Fig. 3a: Instability for married men, percent differences

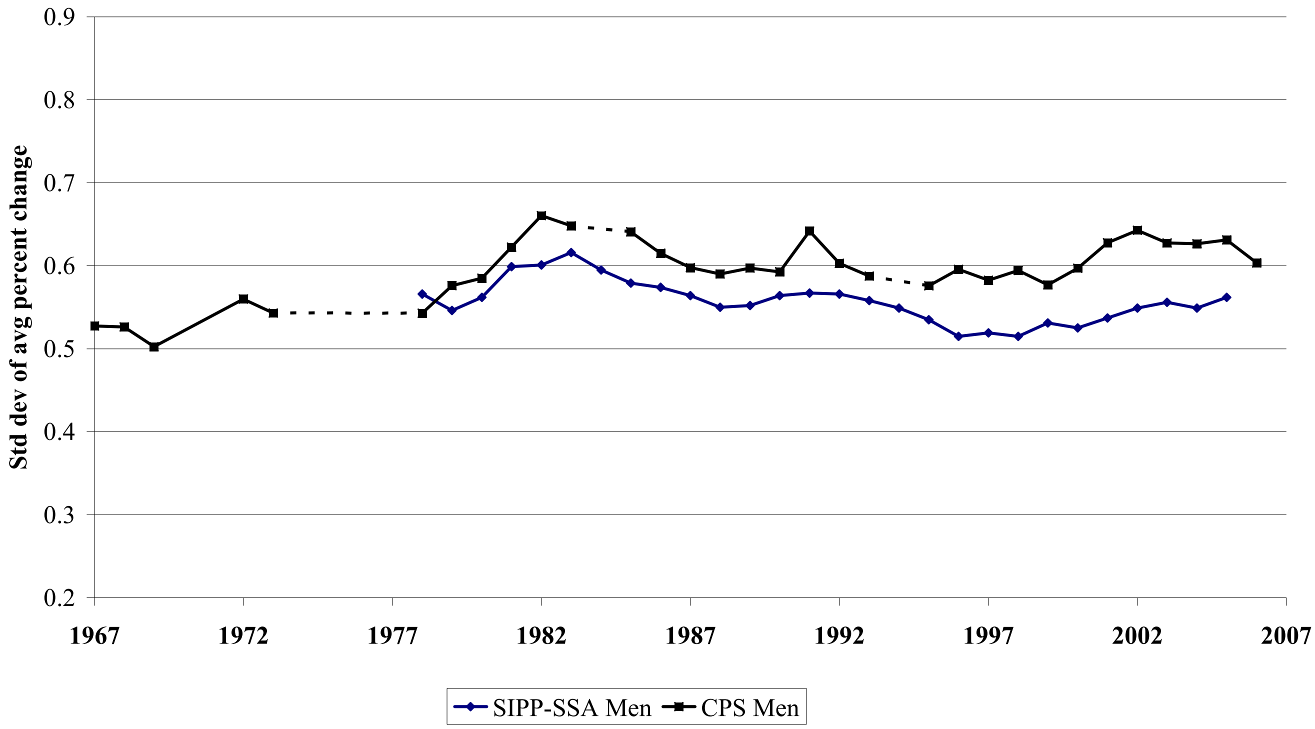

Fig. 3b: Instability for married men, log differences

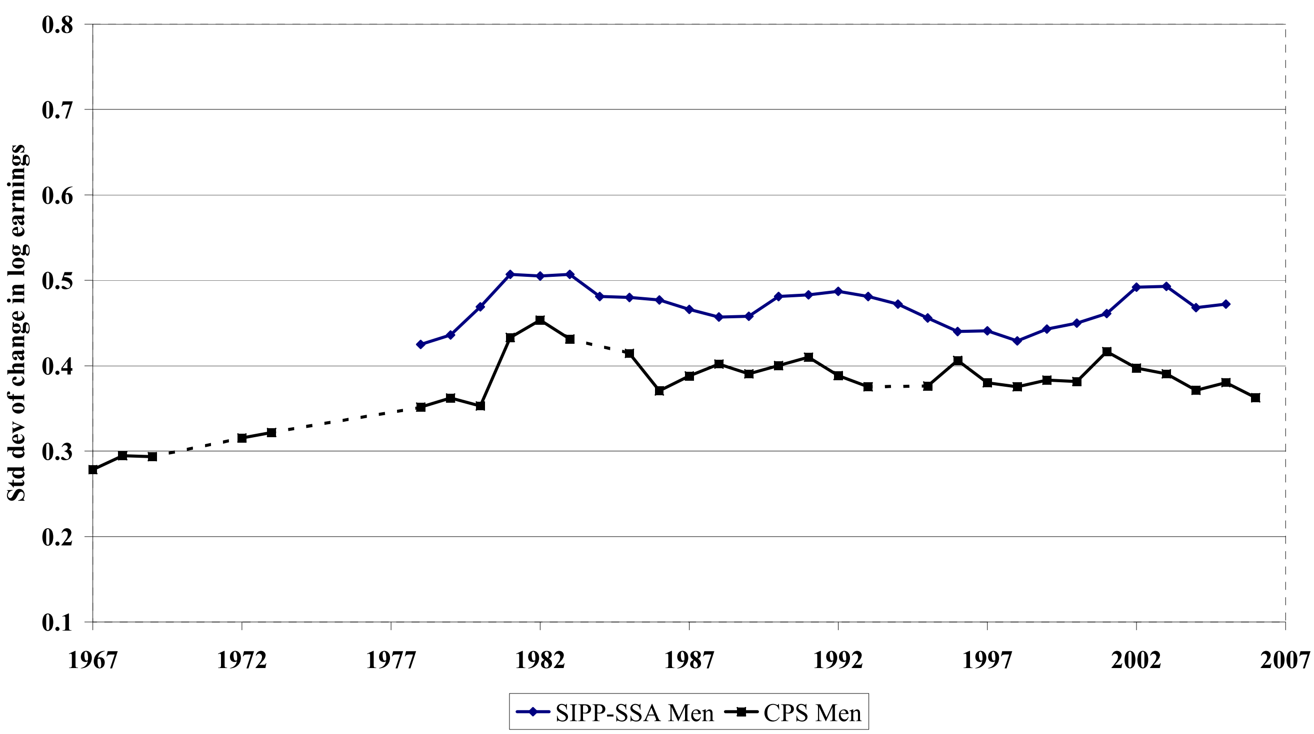

Fig 4a: Instability for married women, percent changes

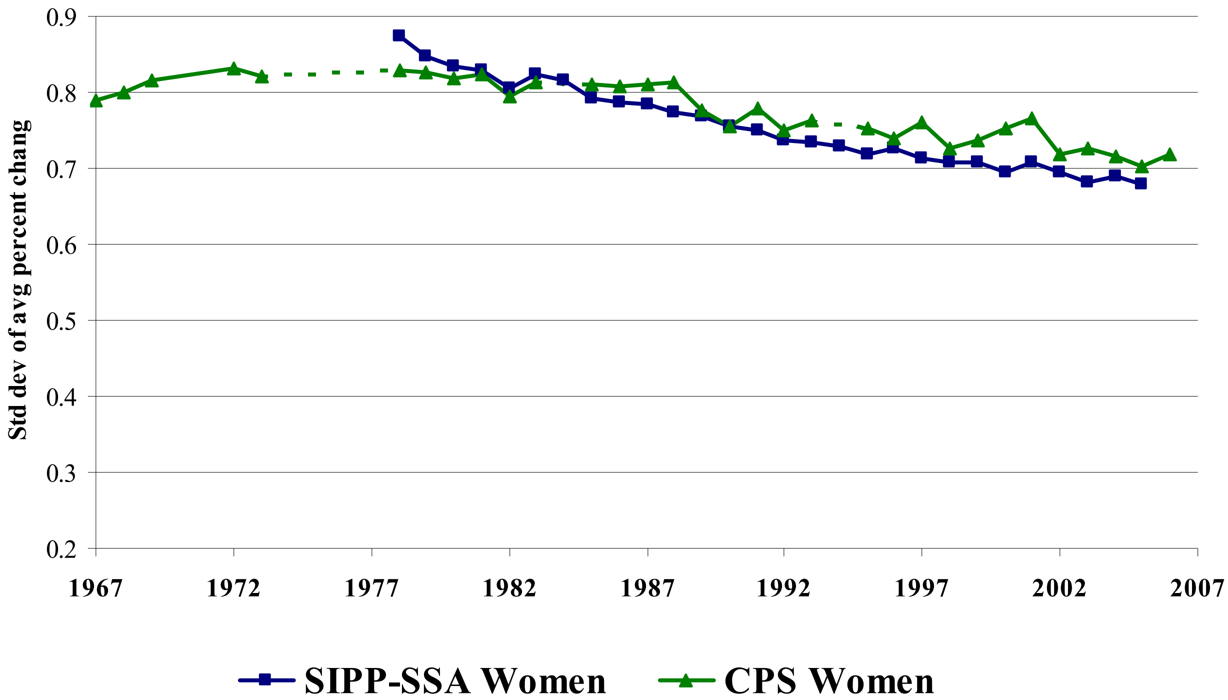

Fig. 4b: Instability for married women, log differences

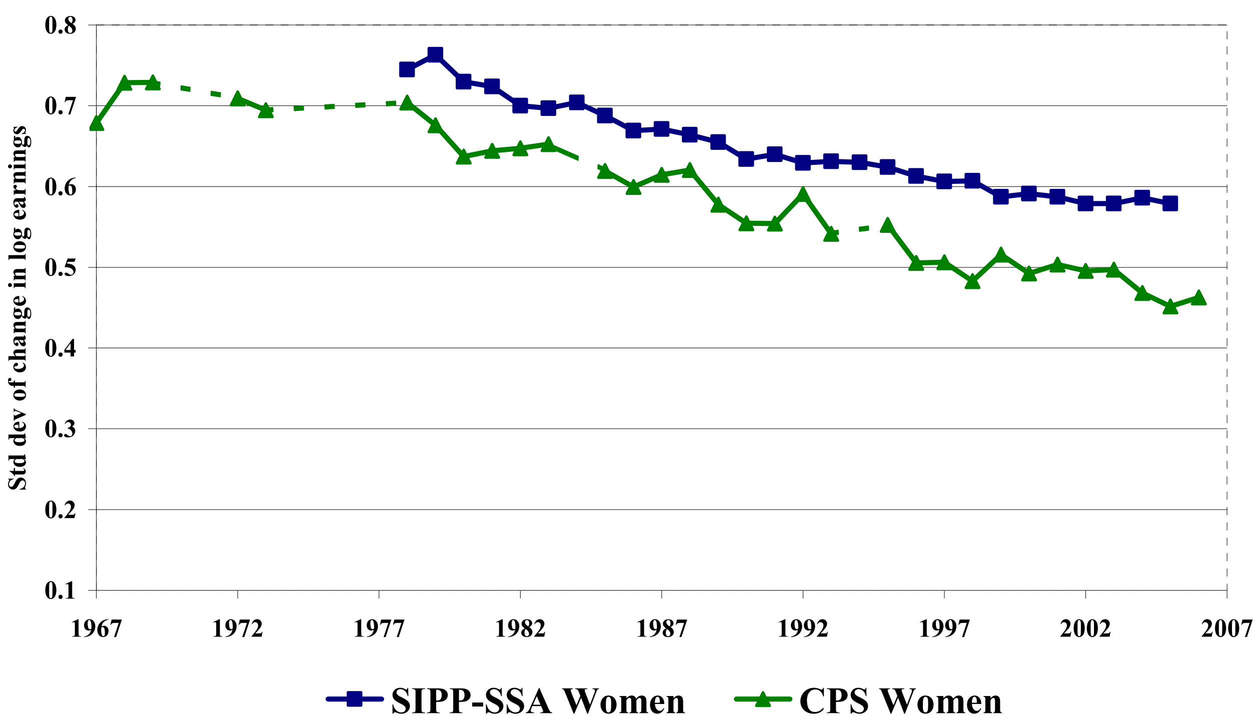

Fig. 5a: Couples instability estimates, percents

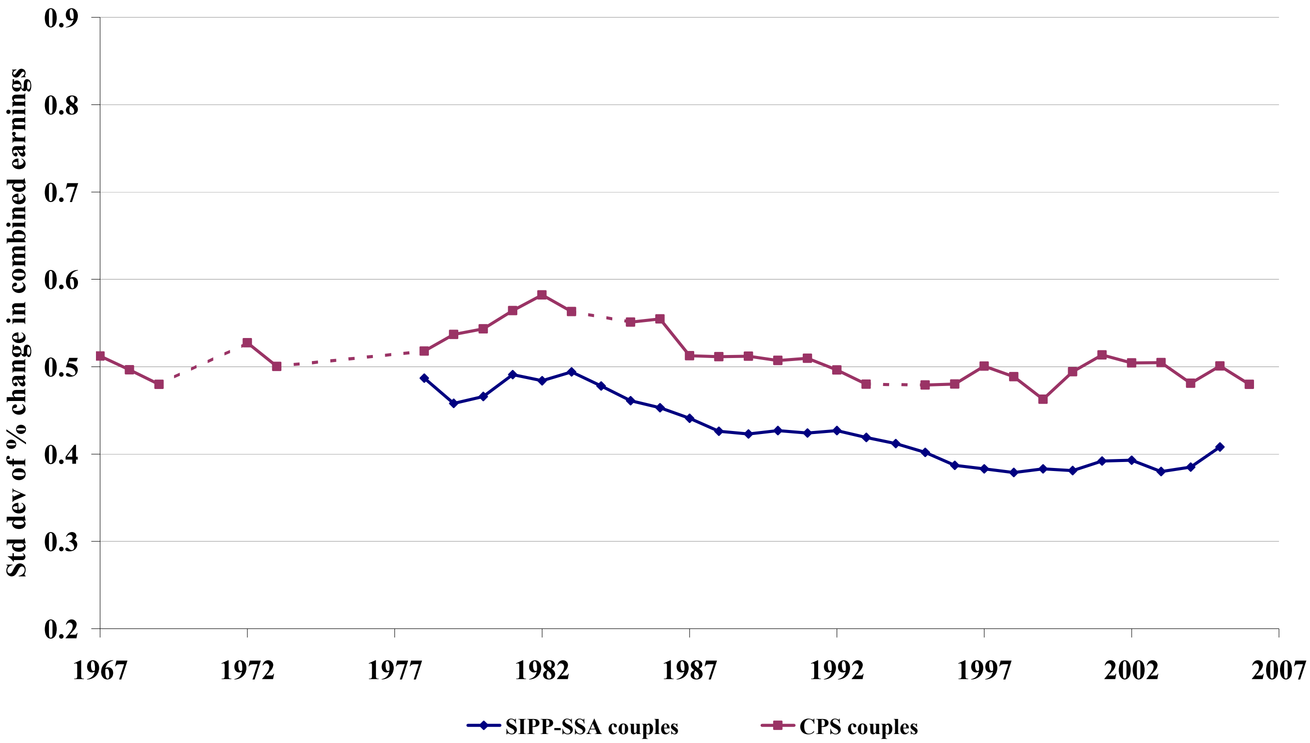

Fig. 5b: Instability for couples, logs changes

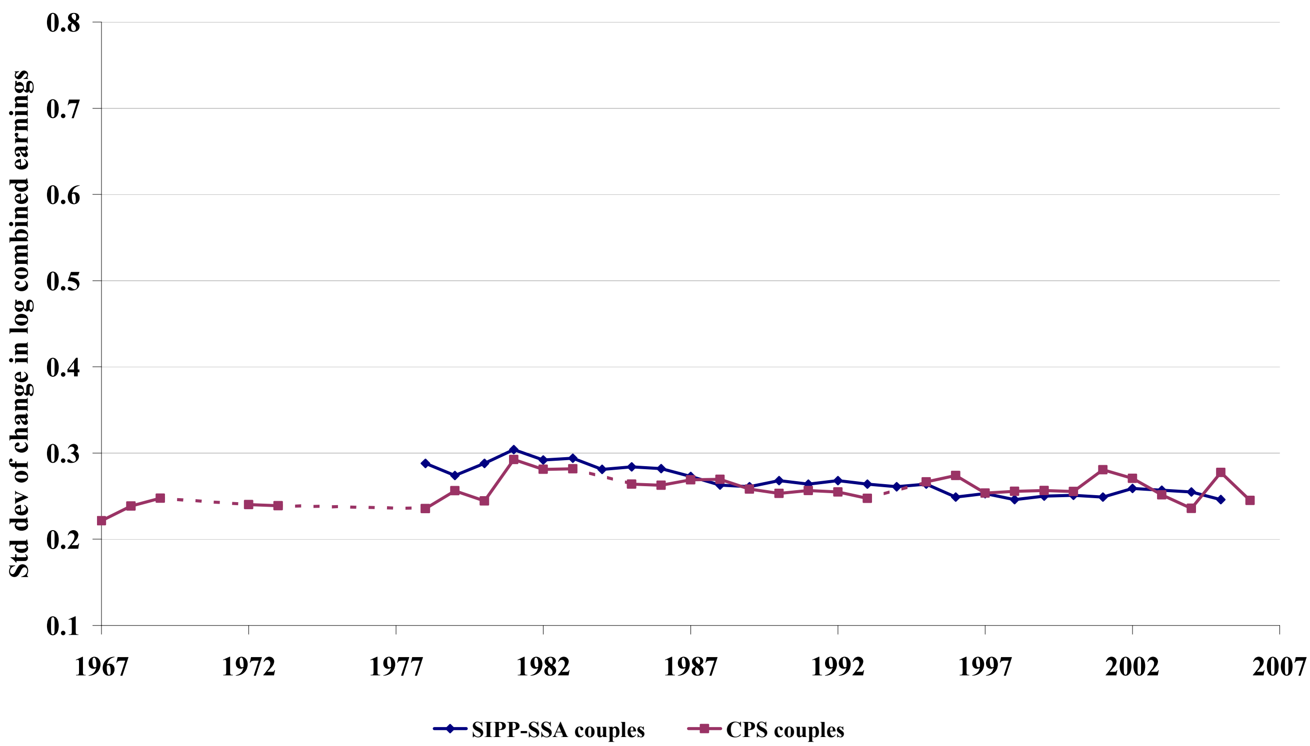

Fig. 6a: Correlation of Spouses' Percent Earnings Changes

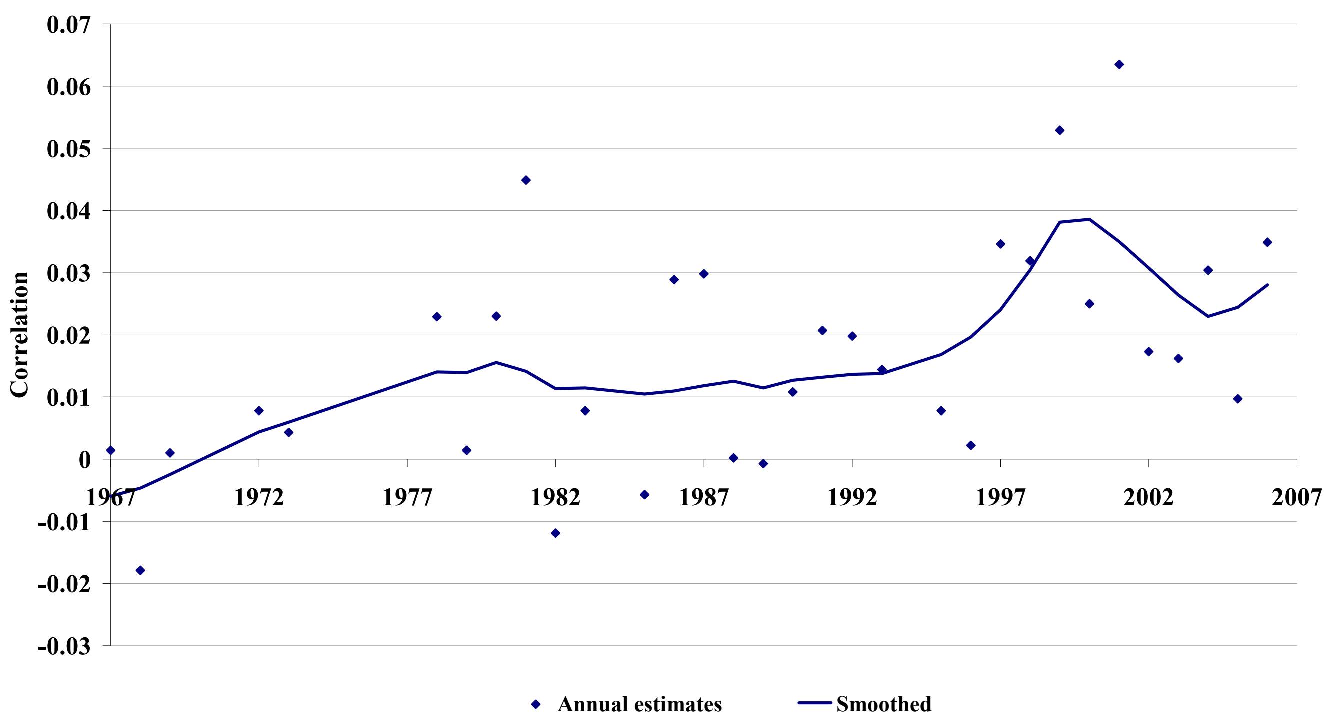

Fig. 6b: Correlation of Couples' Log Earnings Changes

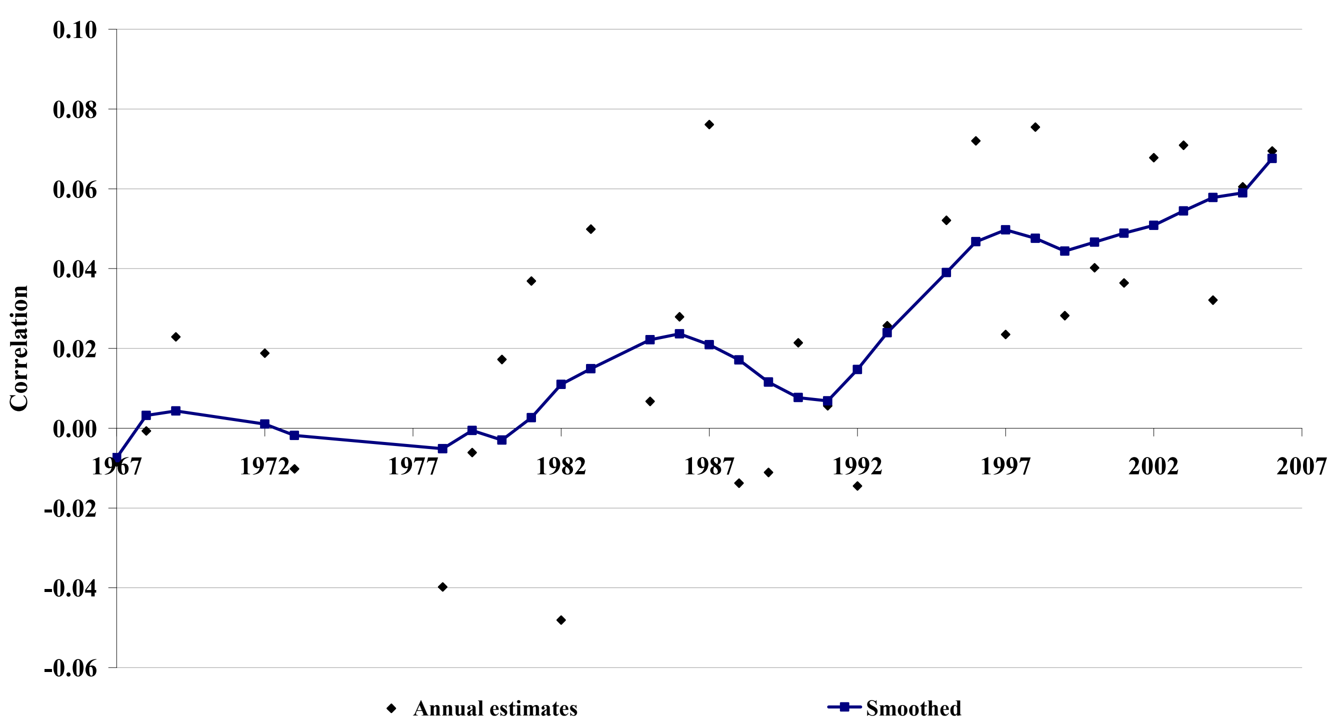

Fig. 7a: Smoothed Correlations of Couples' Percent Changes

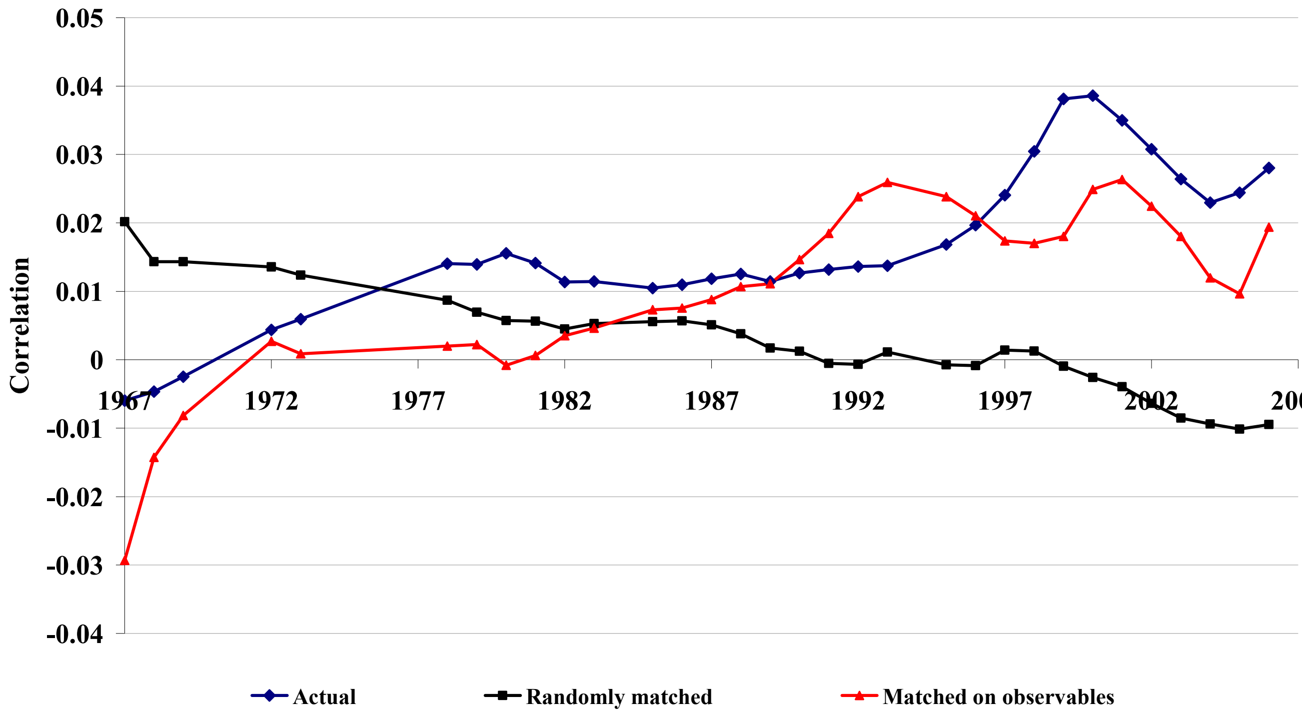

Fig. 7b: Smoothed Correlations of Couples' Log Changes

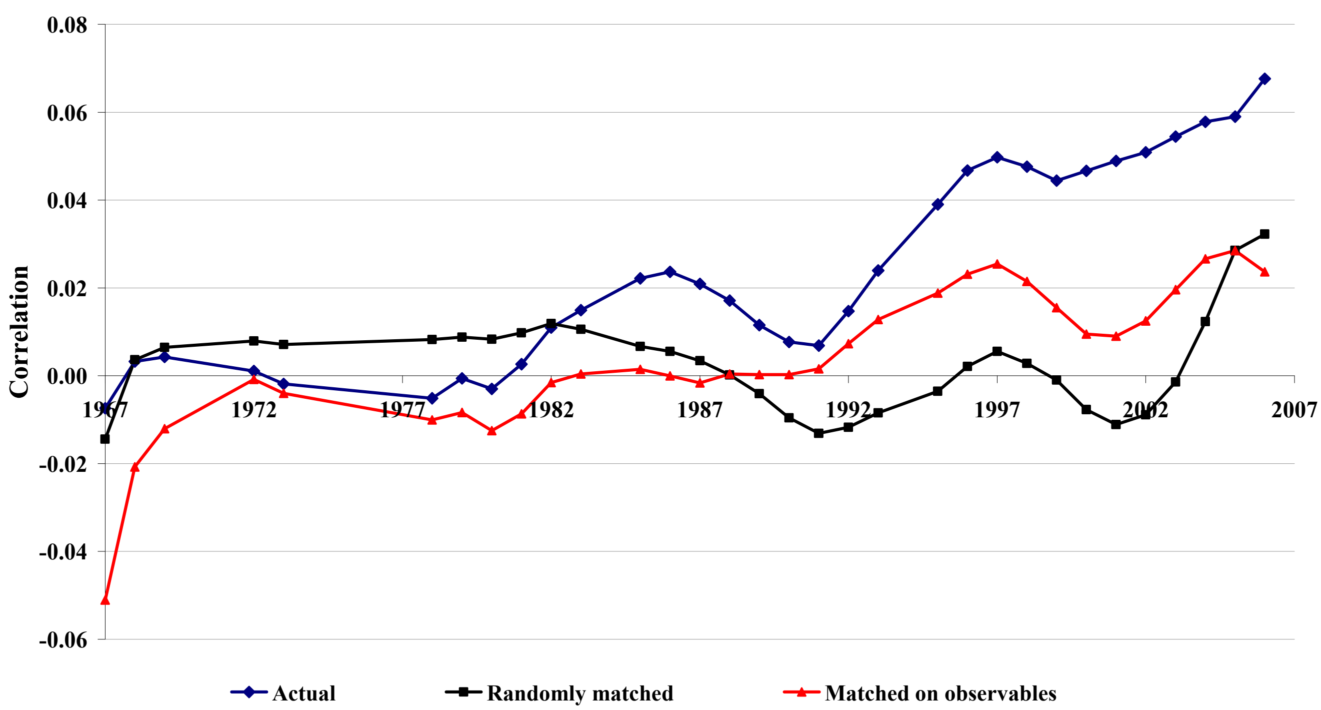

Fig. 8a: CPS couples instability - actual vs. rematched, % changes

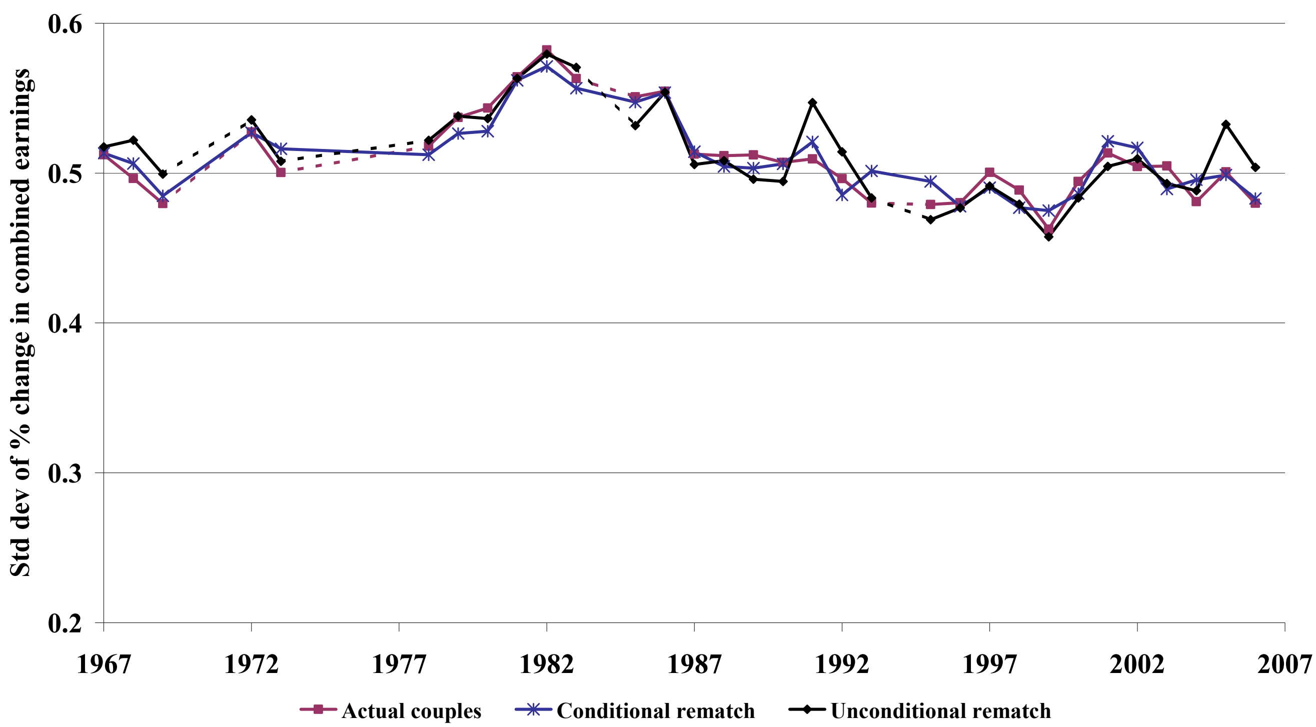

Fig. 8b: CPS couples instability - actual vs. rematched, log changes

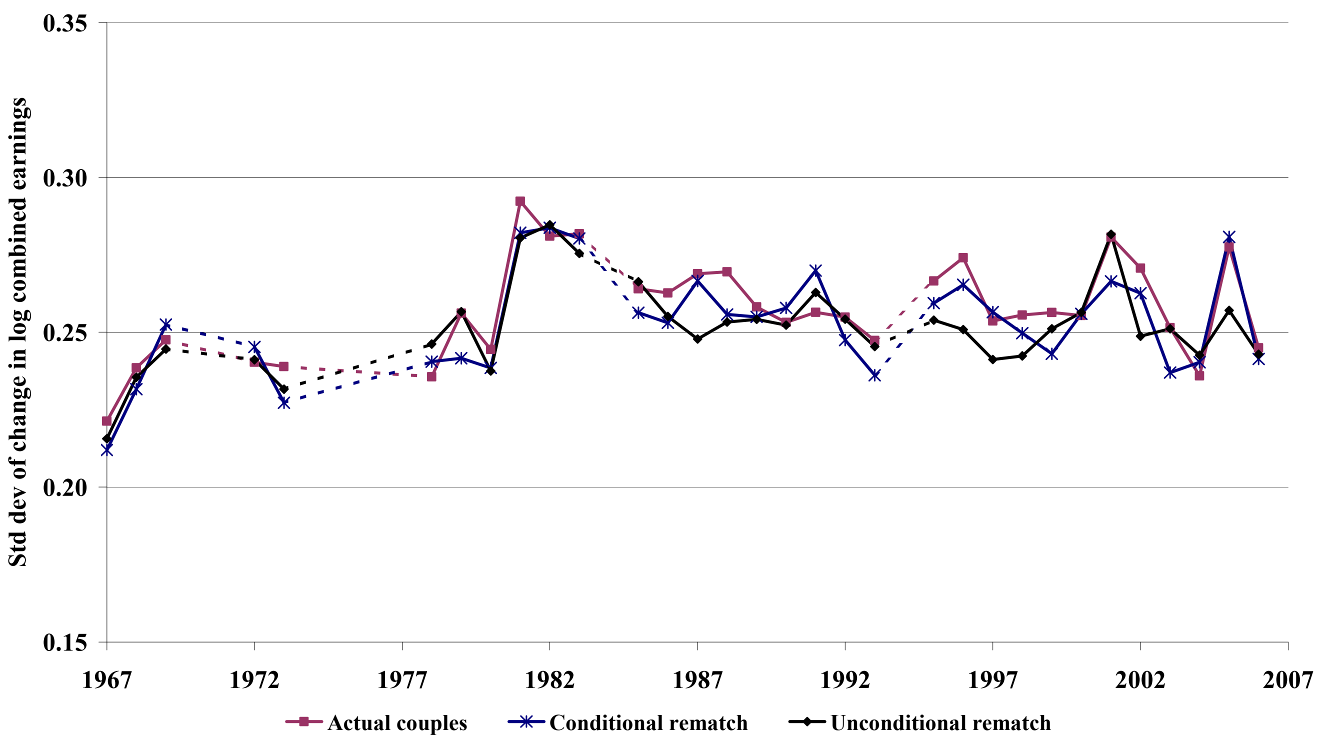

Fig. 9a: SIPP couples instability - actual vs. rematched, % changes

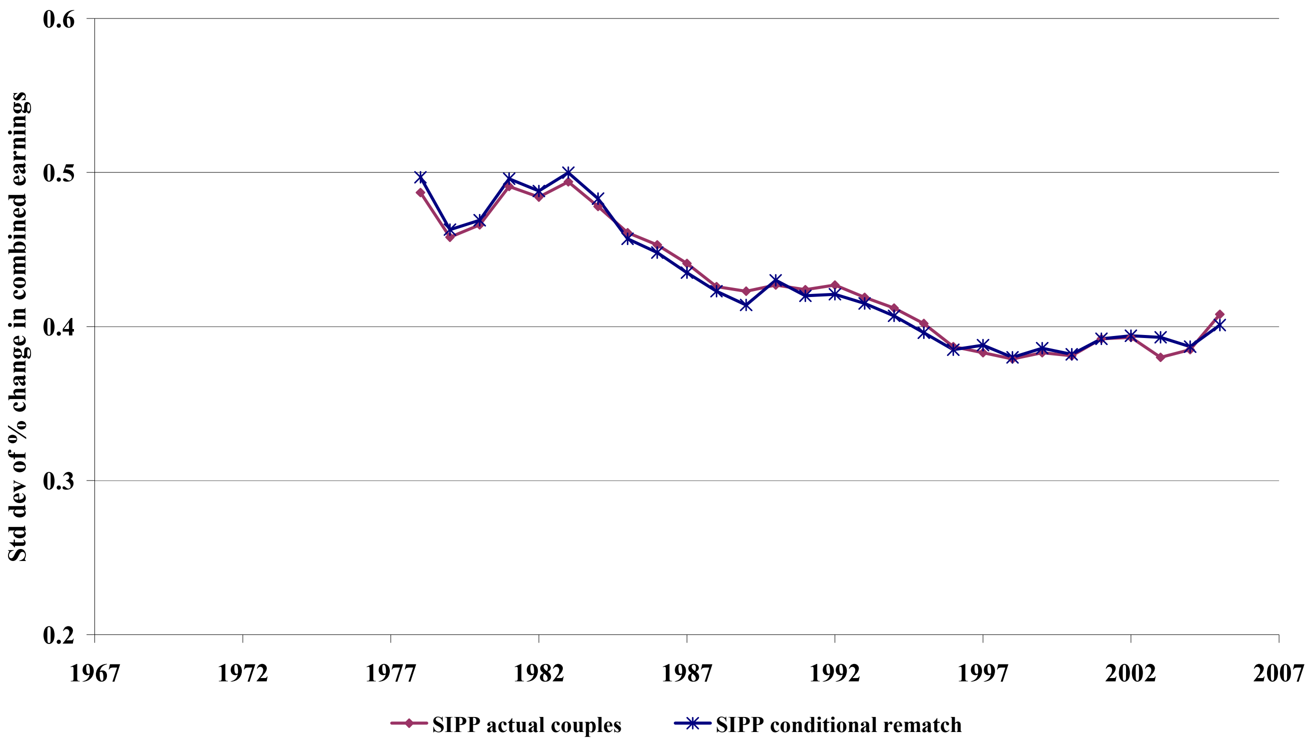

Fig. 9b: SIPP couples instability - actual vs. rematch, log changes