Trends in Earnings Inequality and Earnings Instability among U.S. Couples: How Important is Assortative Matching?*

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Abstract

We examine changes in inequality and instability of the combined earnings of married couples over the 1980–2005 period using two U.S. panel data sets: Social Security earnings data matched to Survey of Income and Program Participation panels (SIPP-SSA) and the Panel Study of Income Dynamics. Relative to male earnings inequality, the variance of couples' earnings is both lower in levels and rises by a smaller amount. We also find that couples' earnings instability is lower in levels compared to male earnings instability and actually declines in the SIPP-SSA data. While wives' earnings played an important role in dampening the rise in inequality and year-to-year variation in resources at the family level, we find that marital sorting and coordination of labor supply decisions at the family level played a minor role. Comparing actual couples to randomly paired simulated couples, we find very similar trends in earnings inequality and instability.

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1 Introduction

The U.S. labor market experienced a tremendous rise in male earnings inequality over the past four decades.[1] Not only did cross-sectional earnings inequality increase, the within-person variability of earnings increased as well.[2] Over the same period there was also a large increase in employment and earnings of women, with particularly dramatic changes for married women. Given these concurrent trends, an important question is the extent to which wives' earnings and changes in family labor supply helped mitigate the rise in male earnings inequality and possibly smoothed over the variability of male earnings. On the other hand, a countervailing force is the pattern of positive assortative matching which may have contributed to rise in couples' earnings inequality. In this paper, we address these questions using two different panel data sets of married couples: Social Security earnings data matched to Survey of Income and Program Participation surveys (hereafter, the SIPP-SSA data), and the Panel Study of Income Dynamics (PSID).

Recent papers in the earnings inequality literature have used administrative data sets to reconsider earlier findings based on survey data. Kopczuk, Saez, and Song (2010) use a sample of longitudinal earnings records extracted from Social Security Administration (SSA) data sources to examine individual earnings inequality since 1937 and find a U-shaped pattern. They also find that earnings mobility increased over time largely due to the upward progress of women through the earnings distribution. Using the same data set and pooling men and women, Sabelhaus and Song (2010) find a decline in earnings variability of individual earnings which, as they point out, coincides with the decline in aggregate economic volatility known as the "Great Moderation." While these studies bring new panel data to broaden the study of individual earnings dynamics to include women, they do not consider how inequality and instability of couples' combined earnings have evolved.

Our paper builds on an earlier literature examining the role of family labor supply in earnings inequality. Cancian, Danziger, and Gottschalk (1993), Cancian and Reed (1999), Hyslop (2001), Devereux (2004), Pencavel (2006a), and Pencavel (2006b) examine the impact of wives' earnings on family earnings inequality and find an equalizing impact. Hyslop (2001), in particular, provides a thorough study examining separately the impact of wives on permanent and transitory components of earnings, and allowing for endogenous labor supply responses. One potential drawback to his study is that he selects couples who are continuously employed,

[1]See, for example, survey articles Autor and Katz (1999) and Autor, Katz, and Kearney (2008). More recent papers documenting inequality trends include Blundell, Pistaferri, and Preston (2008), and Heathcote, Perri, and Violante (2010).

[2]Gottschalk and Moffitt (1994) first documented the rise in this latter component, referred to in the literature as "earnings instability." Other papers using alternative data sets 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).

thereby largely ignoring labor supply decisions at the extensive margin. In addition, most of the previous studies have relied on two households surveys—the Current Population Survey and the Panel Study of Income Dynamics (PSID)—to study family earnings dynamics. Our study uses an administrative data source—the SIPP-SSA data—along with the more familiar PSID, allowing us to compare results across these data sources.

Earnings of spouses may co-vary due to coordinated labor supply decisions within the household or due to correlated shocks. 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 life cycle (see Lundberg 1988). Such adjustments imply a negative correlation between husbands' and wives' earnings that may affect both transitory and permanent variances. On the other hand, there is a well-established pattern of positive assortative mating on education (Mare (1991), Pencavel (1988)). As women become more strongly attached to the labor force, marital sorting may result in increasing correlation of spouses' earnings. Along these lines, Greenwood, Guner, Korchakov, and Santos (2014) find positive assortative matching to have been a major contributing factor to rising household income inequality.

To gauge the importance of matching and joint labor supply decisions, we build counterfactual earnings inequality and instability measures by drawing random matches of married men and married women and constructing the same measures using their combined earnings. If earnings inequality and instability measures constructed using the randomly rematched couples differ substantially from those of actual couples, this would point to an important role for matching and/or joint labor supply decisions. Our findings are as follows:

1. We find that inequality in the combined earnings of couples grew over the 1980–2005 period based on evidence from both the PSID and the SIPP-SSA data. Inequality of couples' combined earnings is lower than inequality of husbands' earnings, and while it has grown over time, it has done so more slowly than inequality of husband's earnings.

2. Instability of couples' earnings actually declined in the SIPP-SSA data while it started at a lower level but increased in the PSID. In both data sets, however, earnings instability is lower for couples than for husbands and rises by a smaller amount (PSID) or falls by a larger amount (SIPP-SSA) compared to male earnings instability.

3. We find that coordination of spouses' labor supply decisions and positive assortative matching play a minimal role in determining overall earnings inequality and earnings instability among couples. We find very similar trends for actual and simulated couples,

suggesting that who is married to whom is relatively unimportant for the evolution of couples' inequality and instability in the U.S.

The rest of the paper is structured as follows. Section 2 discusses the methodology while Section 3 describes our data sets and the samples used. Section 4 describes earnings instability and inequality trends for individuals. Section 5 then presents evidence on these trends for couples. Section 6 compares inequality and instability measures across actual and simulated couples to examine the importance of spousal matching and family labor supply decisions. Section 7 examines the robustness of our results to alternative sample restrictions used by other authors. Section 8 summarizes our findings and describes our plans for future work.

2 Methodology

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

$$\begin{aligned} \log y_{it} &= X'_{it}\beta_t + \epsilon_{it} \\ \epsilon_{it} &= p_t^{\mu}\mu_{it} + p_t^{v}v_{it}, \end{aligned} \tag{1}$$

where y_{it} denotes individual i's annual earnings and X_{it} denotes observed characteristics such as age and education. Residual earnings, ϵ_{it}, are assumed to consist of a permanent component, μ_{it}, and a transitory component, v_{it}, which is assumed to be independent of μ_{it}.[3] The term p_t^{μ} represents factor-loading on the person-specific permanent component, such as return to individual skills or human capital, which may vary by year. Similarly, the term p_t^{v} reflects factor-loading on the person-specific transitory component. The transitory component, v_{it}, may comprise of purely transitory i.i.d. shocks and/or a serially correlated transitory process. In the data, much of the variation in individual earnings is due to the variation in ϵ_{it}. Understanding the cross-sectional variation of ϵ_{it} is, therefore, important for understanding the cross-sectional variation of earnings, y_{it}. In the following, we refer to the cross-sectional variance of residual earnings, ϵ_{it}, as "earnings inequality." We include a polynomial in age in X_{it} to control for the predictable life-cycle effects and year dummies to control for aggregate trends in earnings, but leave returns to other observable characteristics such as education in our measure of inequality. Our measure of inequality, therefore, will reflect earnings inequality due to idiosyncratic individual labor market experiences as well as earnings inequality due to differential returns to observable characteristics among individuals of the same age.

To gauge the importance of permanent versus transitory components of earnings inequality we follow the methodology of Kopczuk, Saez, and Song (2010). In particular, define the

[3]The permanent component is normally modeled as a person-specific fixed effect, or a sum of the fixed effect and a martingale component.

average of ϵ_{it} in a five-year window as $\bar{\epsilon}_{it} = \sum_{j=t-2}^{j=t+2} \epsilon_{ij}$. Following Kopczuk, Saez, and Song (2010), we refer to the cross-sectional variance of $\bar{\epsilon}_{it}$, $\text{var}^i(\bar{\epsilon}_{it})$, as the "permanent variance" at time t, and the cross-sectional variance of $\epsilon_{it} - \bar{\epsilon}_{it}$ as the "transitory variance" at t. To interpret the measures, consider the case when μ_{it} is a time-invariant person-specific effect μ_i, the factor-loadings p_t^{μ} and p_t^{v} are constant, and v_{it} is an i.i.d. shock. The variance of $\bar{\epsilon}_{it}$ will then come close to the variance of the permanent component, μ_i, provided that a five-year average of the transitory shocks v_{it} has negligible variance. In a more general case, when the permanent component is modeled as a random walk or a highly persistent process, the variance of $\epsilon_{it} - \bar{\epsilon}_{it}$ may contain the contribution of both permanent and transitory shocks, as also noted by Kopczuk, Saez, and Song (2010). However, $\bar{\epsilon}_{it}$ will put a larger weight on shocks to the permanent component, more so if the averaging window is larger.[4]

We further expand our statistical model of earnings to apply to couple c:

$$\begin{aligned} y_{ct}^m &= X_{ct}^m \beta_t + \epsilon_{ct}^m \\ \epsilon_{ct}^m &= p_t \mu_{ct}^m + v_{ct}^m \\ y_{ct}^f &= X_{ct}^f \beta_t + \epsilon_{ct}^f \\ \epsilon_{ct}^f &= p_t \mu_{ct}^f + v_{ct}^f, \end{aligned} \tag{2}$$

where the superscripts m and f refer to the husband and the wife respectively. The residual variance of couples' earnings will reflect the variances of the head's and wife's permanent and transitory components as well as the covariances between their permanent and transitory components. In practice, we run a regression of (log of) $y_{ct}^m + y_{ct}^f$ on a polynomial in head's age and year dummies. Our residual, ϵ_{ct}, is, therefore, a combination of residual earnings of the head and wife.

As with our previous measures, we use the variance of ϵ_{ct} averaged over a five-year window to measure the permanent variance of couples' earnings, while the variance of $\epsilon_{ct} - \bar{\epsilon}_{ct}$ measures the transitory variance at time t. The permanent variance of couples' earnings, call it $\psi_{\bar{\epsilon}_{ct}}$, will include the effects of matching and coordinated changes in labor supply, as well as the effects of combining income draws from two distributions with differing properties. Due to positive assortative mating, we expect matching to raise inequality. In addition, the impact of positive assortative matching on earnings inequality may have increased over time due to rising labor force participation of women. Even if the most able men and women are matched to each other, this will likely have little impact on couples earnings inequality if women do not participate in the labor force. As women participate in the labor force, the most able women

[4]Note, however, that there is a tradeoff in selecting a wider window—the wider window will be more informative on the rise of inequality due to permanent or more persistent shocks but it also entails selecting a sample of more stable couples which is likely to be less representative of the overall population of U.S. families.

married to the most able men are likely to have higher earnings relative to the less able women married to less able men. These channels are highlighted in a recent paper, Greenwood, Guner, Korchakov, and Santos (2014). In contrast to matching, coordinated labor supply is expected to reduce inequality as women may compensate for husband's job loss or specialize in home production while husbands specialize in working outside the home.

To gauge the importance of matching and joint labor supply decisions, we build counterfactual permanent variances by drawing random matches of married men and married women and constructing the same measures using their combined earnings. First, to isolate the effect of joint labor supply decisions from marital sorting, we build a counterfactual permanent variance, $\psi^1_{\bar{\epsilon}_{ct}}$, by grouping couples based on observable characteristics such as education of the husband and wife and age of husband and wife in addition to year, and randomly matching couples within groups.[5] We refer to these re-matched couples as "conditionally swapped" couples. Since the difference between the actual variance and this counterfactual variance isolates the role of offsetting joint labor supply, we expect $\psi^1_{\bar{\epsilon}_{ct}}$ to be higher than the actual variance.[6]

To further isolate the role of matching, we build a second counterfactual variance, $\psi^2_{\bar{\epsilon}_{ct}}$, by randomly re-matching married men and married women in a given year without conditioning on either education or age. We refer to these re-matched couples as "unconditionally swapped." The difference between "conditionally swapped" and "unconditionally swapped" couples reflects matching so we expect the counterfactual variance $\psi^2_{\bar{\epsilon}_{ct}}$ to be lower than $\psi^1_{\bar{\epsilon}_{ct}}$. The difference between "unconditionally swapped" and actual, $\psi_{\bar{\epsilon}_{ct}} - \psi^2_{\bar{\epsilon}_{ct}}$, reflects the net impact of both matching and joint labor supply. We construct analogous measures for the transitory variance, allowing us to similarly isolate the roles of matching and joint labor supply.

[5] More precisely, we define 13 education classifications for the couple based on cross-classification of five education classes for the husband (less than high school, high school graduate, some college, college graduate, more than college) with classification of wife's education as less than/equal to/greater than the husband's education. 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 (13×9) groups for each year. 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. For the PSID sample, since it is smaller, we define four age groups and four education groups. The age groups are based on whether the head and wife are aged below 40 or above 40; the education groups are based on whether the head and wife have more than 12 years of schooling, or 12 years of schooling or less. We have examined the results of using these more aggregate categories with the SIPP-SSA data and find that the results are very similar to those based on the more detailed categories.

[6] The assumption here is that observable characteristics such as education and age sufficiently control for matching. It is possible that husbands and wives match on characteristics we do not observe in the data. It may also be the case that husbands and wives experience (positively) correlated shocks due to local labor market conditions. Both of these effects would work against us finding the negative correlation due to joint labor supply decisions.

3 Data

3.1 SIPP-SSA matched data

Our first data set combines confidential administrative earnings records with Survey of Income and Program Participation (SIPP) survey data. The SIPP is a series of nationally representative U.S. panel data sets, with sample sizes ranging from about 14,000 to 52,000 households per panel. Each of the panels we use collects information in 8-12 four-month waves, over a 32- to 48-month period. Our sample of individuals is drawn from respondents to the 1990–1993, 1996, 2001, and 2004 SIPP panels.[7] Our sample of individuals with linked earnings records includes only those respondents who provided the information needed to validate matches to Social Security Administration (SSA) earnings records. For these individuals, we have annual earnings for 1978–2006 based on 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 data collected in the SIPP. Age and gender are based on combined information from the SIPP and SSA sources.

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 annual earnings for each year between 1978 and 2006. Our base sample includes all matched SIPP respondents in any years in which they meet the 25–59 age restriction. Thus for someone who was 50 when interviewed in the 1990 SIPP panel, we use earnings for 1978–1999, while for someone who was 20 in 1990 we use earnings for 1995–2006. In total we have about 5 million person/year observations, or roughly 170,000 people per year.

Where we condition on marital status, we only use earnings for years in which we can determine whether or not someone is married. The marital history information collected in the second wave of each SIPP panel, along with updates from changes in later waves of that panel, gives us information on an individual's marital status for years leading up to and during that individual's SIPP panel. While we have earnings for years after the earlier panels are over, we do not know marital status for those years. 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 principle use data on any matched person born between 1919 and 1953 from

[7] The 1990-1992 panels contain eight waves, the 1993 and 2001—nine, and the 1996 and 2004 panels contain twelve waves.

any of our 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 if they are in the same household in the second wave of their SIPP panel. For a sample member who had a marriage that ended 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 do not have any information on their former spouse. Thus we cannot, for example, look at the combined couples earnings during former marriages because we are missing earnings for their former spouse. For this reason, in our estimates for both actual and counterfactual couples, we use data only on members of couples with linked earnings for both spouses.[8]

3.2 PSID data

Our second data set is the Panel Study of Income Dynamics (PSID) which has been used in numerous empirical papers to document trends in earnings inequality and instability in the U.S. Given its importance in this literature, results from the PSID provide an important point of comparison for our findings from the less familiar SIPP-SSA administrative earnings data. The PSID was initiated in 1968, interviewing a sample of about 5,000 families representative of the U.S. population (the SRC sample) and a sample of about 2,000 low-income families (the Survey of Economic Opportunity sample). The PSID has followed the original families and their offspring over time, collecting information on earnings, marital status, and a number of other topics. Interviews were conducted annually up to 1997 and have been conducted biennially since then. We use information for the SRC sample during 1978–2007 for our current results.

3.3 Sample Selection

We make the following sample restrictions in constructing our estimates of both inequality of permanent earnings and earnings instability. For our male samples, we select men who are 25-59 years old and had non-zero earnings. We also minimize the effect of outliers by deleting the bottom and top 1 percent of earnings observations. Men in our sample have to satisfy the above conditions for all years of the window in question— so for the five-year window surrounding year t, men must satisfy the above conditions for the 2 years before and after t, as well as for year t itself. For our couples samples, we begin with husbands who satisfy the

[8]This means that long-duration marriages will be over-represented in our sample, as a woman married in 1980 and interviewed in the 2004 SIPP panel will be included in our couples' sample if still married in 2004, but not if she divorced or became a widow in the intervening years. We do have earnings, education, and age for both men and women who are interviewed after a marriage has ended, but not information on their former spouse.

above conditions. We further require that couples be continuously married to each other over the relevant window and that the wife also satisfies the 25-59 age range in each year. Since our focus is on wives' contributions to couples earnings through both wages and labor supply, we include wives who have zero earnings. This restriction is typically used in the models which assume full-time working males and females making labor supply decisions at both the extensive and intensive margins—see, for example, Attanasio, Low, and Sanchez-Marcos (2008) and Heathcote, Storesletten, and Violante (2010). We explore sensitivity of our results to alternative restrictions on male labor supply in Section 7.

4 Trends in Individual Earnings Inequality and Earnings Instability

We begin by presenting estimates for men's earnings. Estimates for all men are useful as a check for consistency with others' findings, but we also look at husbands separately because their earnings directly contribute to couples' earnings.

Figure 1 shows the well-known rise in the permanent variance of male earnings that has been documented in numerous studies. The top panel gives estimates based on the SIPP-SSA data while the bottom panel gives estimates based on the PSID. Note that our SIPP-SSA data begin with the 5-year average centered on year 1980 and end with 2004. The PSID data begin with the 5-year average centered on 1980 and end with the 5-year average for 2005 which includes data through 2007. After 1997 the PSID switched to biennial reporting which makes comparability difficult. In addition, the PSID went through a major overhaul between the 1993 and 1994 surveys, switching to computer-assisted telephone interviewing, automated editing of data, and changing the income questions. Thus, the changes encompassing these years have to be interpreted with caution.[9]

While the levels of the permanent variance differ across the two data sets (higher in the SIPP-SSA, perhaps because the PSID measure of labor income includes additional components that smooth the income from wages and salaries), both data sets show an increase in trend. In the SIPP-SSA data, the variance increased by 70 percent over the period 1980-2004 for all men and by 74 percent for husbands (see Table 1). In the PSID, variance increased by 85 percent for all men and by 71 percent for husbands over the same period.

Figure 2 describes transitory earnings variation among all men and among husbands. As documented in Dynan, Elmendorf, and Sichel (2012) and Shin and Solon (2011) and illustrated in the bottom panel of Figure 2, earnings instability of men was stable during the 1980s but rose in the 1990s and 2000s in the PSID. In contrast, there is cyclical variation in male earnings

[9]See discussion in Dynan, Elmendorf, and Sichel (2012).

instability in the SIPP-SSA but little trend. This pattern is also found by Kopczuk, Saez, and Song (2010) and Dahl, DeLeire, and Schwabish (2008). Comparing across data sets, Celik, Juhn, McCue, and Thompson (2012) find that the recent rise in volatility found in the PSID is somewhat anomalous.

5 Trends in Earnings Inequality and Earnings Instability of Couples

How do inequality and instability of couples' earnings compare to those for husbands? Figure 3 gives a comparison of the trends in the permanent variances, with the corresponding numbers appearing in Table 1. According to the SIPP-SSA data, inequality of couples' earnings is both lower in levels and has increased at a slower rate since 1980. In 1980, the variance of couples' earnings is approximately 5 percentage points lower. In 2004, it is 12 percentage points lower. Over the period, the permanent variance of couples' earnings rose by approximately 57 percent while the permanent variance of husbands' earnings rose by 74 percent. While overall levels of inequality are lower in the PSID, the trends are similar, as illustrated in the bottom panel. In the PSID, couples' earnings variance increased by 46 percent from 1980 to 2005 while husbands' earnings variance increased by 71 percent.

Figure 4 and Table 2 present estimates of the instability of couples' combined earnings along with instability of husbands' earnings. Couples' earnings have lower levels of instability than the earnings of husbands alone. As we similarly found for individual earnings, the two data sets show different trends in the instability of couples' earnings over this period. The SIPP-SSA estimates suggest that instability of couples earnings has actually *fallen* since 1980, while the PSID shows an increase. Even in the PSID, however, the increase in instability of couples' earnings is more muted than the increase in instability of husbands' earnings.

Comparison of male earnings with couples' earnings suggests that wives have played a significant role not only in mitigating the rise of permanent earnings inequality but also in smoothing over earnings instability at the family level. In the next section we explore to what extent coordinated labor supply decisions and positive assortative matching contributed to, or possibly hindered, this outcome.

6 The Impact of Coordination and Matching on Couples' Earnings Inequality and Instability

To gauge the importance of marital sorting and coordination, we now turn to comparing earnings instability and inequality measures of actual couples to our counterfactual estimates based on randomly matched couples.[10] We start by defining a sample of eligible husbands and wives for a given five-year window using the same exclusion restrictions described above. We then use random sampling to select a pseudo-wife for each husband for that particular window, drawing wives from the same set of couples. For "conditionally swapped" couples, we draw a random wife that matches the head's wife in education and age group. For "unconditionally swapped" couples, we draw a random wife from the entire set of eligible couples. We then combine the husband's and pseudo-wife's earnings to obtain combined earnings for the rematched couple for years $t-2$ to $t+2$. We regress that earnings measure on a fourth degree polynomial in age and year dummies. Residuals from this regression are then used to construct permanent and transitory variances for each simulation.

Figure 5 illustrates the permanent variance of actual couples' earnings as well as earnings of rematched couples. We find that relative to unconditionally matched couples, conditionally matched couples have higher variance of combined earnings, reflecting positive assortative matching on education and age. Relative to the conditionally matched couples, actual couples have slightly lower variance of earnings which is consistent with coordinated offsetting labor supply behavior. That is, comparing couples within a group defined by the ages and education levels of both spouses, husbands with relatively high earnings tend to have wives with relatively low earnings. But this pattern is not particularly strong. The key observation to take away from these graphs is that relative to the gap between male earnings variance and couples' earnings variance, the differences between the other three lines are very small.

Table 1 shows that in the SIPP-SSA data, actual couples' earnings variance increased by about 56 percent from 1980 to 2004. If we randomly match couples, thereby shutting down positive assortative matching and joint labor supply behavior, couples' earnings variance increases by about 50 percent. Given that both measures start at similar levels, this suggests that about 6 out of the 56 percent rise can be attributed to the combined effects of matching and joint behavior. We reach similar conclusions on examining the PSID in the bottom panel.

[10] While we focus on the variance of log earnings to make our results comparable to many of the previous studies, that measure does not neatly decompose into terms involving the contributions of each spouse plus a covariance term since our samples also include spouses with zero earnings. It may be instructive to consider the following decomposition of couples' earnings based on the squared coefficient of variation, which does have this feature. Letting y denote the level of earnings:

$$\begin{aligned} \mathrm{CV}^2\left(y_{ct}\right) &= \frac{\mathrm{var}(y_{ct})}{\left(\bar{y}_t\right)^2} = \frac{\mathrm{var}(y^m_{ct}) + \mathrm{var}(y^f_{ct}) + 2\mathrm{cov}(y^m_{ct}, y^f_{ct})}{(\bar{y}^m_t + \bar{y}^f_t)^2} \\ &= \frac{(\bar{y}^m_t)^2}{(\bar{y}^m_t + \bar{y}^f_t)^2}\mathrm{CV}^2(y^m_{ct}) + \frac{(\bar{y}^f_t)^2}{(\bar{y}^m_t + \bar{y}^f_t)^2}\mathrm{CV}^2(y^f_{ct}) + \frac{2\mathrm{cov}(y^m_{ct}, y^f_{ct})}{(\bar{y}^m_t + \bar{y}^f_t)^2}. \end{aligned}$$

One can decompose this measure of inequality in couples' earnings into terms involving inequality measures for husbands and wives plus a covariance term. The covariance term incorporates the effect of positive assortative matching and offsetting labor supply behavior. When we randomly rematch couples, we effectively set this covariance term to zero. The difference between inequality measures of actual couples and those of simulated couples will indicate the importance of couple-specific matching and joint behavior.

The differences in trend between the actual and the simulated couples are even smaller.

Assortative matching should manifest itself in high correlation of spousal permanent earnings. In Figure 6, we plot the trends in the correlation of five-year averages of the husband's and his spouse's earnings in PSID data, where the spouse is either actual or randomly drawn.[11] For actual couples, we find that spousal earnings is positively but weakly correlated with each other, and we don't find any distinctive trend in the correlation over time. Similarly, conditionally matched couples have low but positively correlated earnings which suggests that age and education capture the general pattern in assortative matching well. As expected, unconditionally matched couples' earnings do not correlate on average. If higher inequality of family earnings is a result of stronger assortative matching, one should expect that the level of family inequality among actual couples gets higher relative to the level of inequality among unconditionally matched couples. However, this is not the pattern we observe in Figure 5, which corroborates our earlier conclusion that neither assortative matching nor coordinated spousal labor supply decisions are of first order importance for the evolution of inequality in family earnings.

Figures 7 and 8 repeat the comparison, splitting the sample into couples with "less educated" and "more educated" husbands, respectively.[12] The corresponding numbers are presented in Table 3 and Table 4. We find that the overall difference in permanent earnings variance between actual and conditionally matched couples comes primarily from couples with more educated husbands. As shown in Table 4, the variance of earnings for conditionally matched couples is higher than that for actual couples suggesting that there may be offsetting labor supply behavior. This labor supply effect appears to have gotten less important over time in the SIPP-SSA data. The variance of couples' earnings for conditionally matched couples rises 54 percent. However the variance of actual couples' earnings rose by 63 percent. But again, the key point is that neither matching nor joint labor supply behavior make particularly large contributions to the rising trend in the permanent variance of couples' earnings.

Figure 9 provides the same comparison across actual and rematched couples for earnings instability. The gap between male earnings instability and couples' earnings instability is even more pronounced relative to the very minor differences between the actual and randomly matched couples.

What conclusions can we draw regarding wives' contributions to earnings inequality and earnings instability among couples? We find that wives' earnings play an important role both in dampening the cross-sectional inequality of resources for married couples, and in offsetting

[11] To accommodate observations with zero female earnings during a five-year window, we take the five-year averages of levels rather than logs.

[12] In our current estimates, we split off the "more educated" in the SIPP-SSA data based on having at least a bachelor's degree, while in the PSID, "more educated" heads have more than 12 years of schooling. "Less educated" are the rest. We will provide consistent estimates in a future draft.

transitory shocks to those resources. This appears simply due to the fact that earnings of spouses are not strongly positively correlated. Surprisingly we find that the covariance of couples' earnings that arises due to positive assortative matching and coordination in labor supply is relatively minor. Wives' earnings have also played a dampening role in the growth of the cross-sectional earnings variance over time. While the variance of wives' earnings increased, it did not increase as rapidly as the variance of male earnings and at the same time the share of wives' earnings increased. Again, among married couples, who was married to whom appears to be of relatively minor importance.

7 Robustness

7.1 Gini coefficients as measures of inequality

We have so far focused exclusively on the variance of (average) log earnings as our measure of permanent earnings inequality. It may be the case, however, that other inequality measures are more sensitive to low or high earnings observations. Heathcote, Perri, and Violante (2010), for instance, point out that Gini coefficients emphasize the top of the earnings distribution while the variances of logs emphasize the bottom part of the earnings distribution. To the extent that matching differentially affects couples in the lower and upper halves of the distribution, we may be understating the importance of matching. To explore this issue, we redo our matching exercise using Gini coefficients as our measure of inequality. These results are shown in Table 5 and Figure 10. As shown in Table 5, the level of inequality is more similar across the two data sets when we use the Gini coefficient as our measure of inequality. One possibility is that the SIPP-SSA contains a higher proportion of low earnings observations relative to the PSID. Over the period, the Gini coefficient for husbands' earnings rises by similar amounts in the two data sets—38 percent in SIPP-SSA and 35 percent in the PSID. The Gini coefficient for couples' earnings begins at a similar level relative to husbands' earnings in 1980 but rises by a smaller amount over time, rising by about 23 percent in SIPP-SSA and by about 25 percent in the PSID. Comparing actual couples to randomly matched couples, we find that positive assortative matching and joint labor supply played a minor role relative to the increase in inequality of husbands' earnings. In the SIPP-SSA data, the Gini coefficient of earnings of randomly matched couples rises by about 19 percent whereas it rose by about 23 percent for actual couples. This suggests that at most 4 out of the 23 percent increase can be attributed to matching and joint labor supply.

7.2 Dropping zero earnings observations for wives

Next, we explore robustness to dropping zero earnings observations for wives, following the restriction used in Hyslop (2001). Relative to the main sample, this selection limits the effect of coordinated labor supply on the evolution of inequality over time by eliminating couples in which wives enter or exit the labor market in response to shocks or predictable changes in the husband's earnings. As in Hyslop (2001), we drop observations with hourly wages of more than 100 real 1980–1982 dollars. The trends for Gini coefficients and permanent variance are plotted in Figure 11. As in the main sample, conditionally matched couples have more unequal incomes than unconditionally matched couples, reflecting the effect of positive assortative matching on inequality. In contrast to the main sample, however, conditionally matched couples are less unequal than actual couples which likely reflects that offsetting labor supply is more operative at the extensive margin, and that this selection drops the couples with high-wage males and non-working females relative to the main sample. Also, in contrast to the main sample, husbands and wives who are permanently attached to the labor force have highly correlated permanent earnings—see Figure 13. Similar to Hyslop (2001), once we select on continuously working couples, actual couples have considerably higher earnings inequality than randomly matched couples suggesting that positive assortative matching contributes importantly to the *level* of permanent earnings inequality. However, as illustrated in Figure 11 we find little contribution of matching to the trend in earnings inequality over the longer period. This is in contrast to Hyslop (2001) who finds that roughly 23 percent of the rise in couples' permanent earnings inequality over the 1979-1985 period is attributable to matching.

7.3 Keeping zero earnings observations for husbands

We further explore robustness to inclusion of men with zero earnings in the sample, making our restrictions similar to those used in Greenwood, Guner, Korchakov, and Santos (2014). Greenwood, Guner, Korchakov, and Santos (2014) find that an increase in assortative matching on education and earnings makes an important contribution to the increase in inequality between 1960 and 2005. It is possible that by restricting the sample to husbands with non-zero earnings, we may be limiting the impact of matching, particularly if husbands with zero earnings are matched to wives with zero or low earnings. We find, however, that this is not the case. Even when we include men with zero earnings, we do not find much difference between actual and randomly matched couples in the PSID—see Figure 12. For this sample selection, there is some evidence of a higher degree of assortative matching since mid-1990s relative to the earlier period—see Figure 13. However, since the correlation between spousal earnings is small, positive assortative matching does not affect much the relative values of inequality levels for actual versus randomly matched couples as shown in Figure 12. This finding is in contrast to the finding of Greenwood, Guner, Korchakov, and Santos (2014) who argue that assortative matching played an important role in the rise of family inequality from 1960 to 2005.

8 Conclusion

In this paper we examined trends in the variance of combined earnings of husbands and wives using two alternative panel data sets: annual Social Security earnings data matched to multiple SIPP panels, and the PSID. We distinguish between variation in short-term changes in earnings (instability) and variation in longer-term averages (inequality). We use random rematching of spouses as a way to tease out the magnitude of the effects of positive assortative matching on observables and coordination of labor supply within families on these trends.

Comparison of male earnings with couples' earnings suggests that wives' earnings have muted the rise of permanent earnings inequality as well as smoothed over earnings instability at the family level. We find, however, that coordination of spouses' labor supply decisions and positive assortative matching played only a minor role in determining overall trends in earnings inequality and earnings instability among married couples.

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Table 1: Permanent variance of earnings

	1980	1990	2000/ 2001	2004/ 2005	%Δ (2004/2005 - 1980)
			SIPP-SSA		
Men	0.310	0.422	0.480	0.528	70.3 %
Husbands	0.270	0.372	0.430	0.470	74.1 %
Couples	0.224	0.293	0.328	0.350	56.3 %
Couples, cond. swap	0.237	0.301	0.335	0.365	54.0 %
Couples, uncond. swap	0.229	0.289	0.316	0.343	49.8 %
			PSID		
Men	0.194	0.274	0.307	0.359	85.1 %
Husbands	0.185	0.235	0.282	0.316	70.8 %
Couples	0.177	0.208	0.225	0.259	46.3 %
Couples, cond. swap	0.173	0.211	0.234	0.256	48.0 %
Couples, uncond. swap	0.173	0.202	0.226	0.251	45.1 %

Table 2: Transitory variance of earnings

	1980	1990	2000/ 2001	2004/ 2005	% Δ (2004/2005 - 1980)
			SIPP-SSA		
Men	0.113	0.118	0.112	0.123	8.8 %
Husbands	0.094	0.099	0.092	0.098	4.3 %
Couples	0.071	0.056	0.050	0.052	–26.8 %
Couples, cond. swap	0.072	0.058	0.051	0.054	–25.0 %
Couples, uncond. swap	0.072	0.059	0.052	0.053	–26.4 %
			PSID		
Men	0.039	0.046	0.084	0.105	169.2 %
Husbands	0.032	0.038	0.069	0.095	196.9 %
Couples	0.025	0.028	0.041	0.054	116.0 %
Couples, cond. swap	0.027	0.028	0.043	0.056	107.4 %
Couples, uncond. swap	0.027	0.028	0.044	0.054	100.0 %

Table 3: Permanent variance of earnings, less educated household heads

	1980	1990	2000/ 2001	2004/ 2005	%Δ (2004/2005 - 1980)
			SIPP-SSA		
Men	0.295	0.391	0.420	0.467	58.3 %
Husbands	0.257	0.344	0.368	0.402	56.4 %
Couples	0.218	0.273	0.284	0.304	39.4 %
Couples, cond. swap	0.226	0.278	0.282	0.319	41.2 %
Couples, uncond. swap	0.226	0.281	0.288	0.314	38.9 %
			PSID		
Men	0.190	0.224	0.233	0.282	48.4 %
Husbands	0.179	0.199	0.189	0.237	32.4 %
Couples	0.176	0.192	0.196	0.226	28.4 %
Couples, cond. swap	0.168	0.180	0.181	0.202	20.2 %
Couples, uncond. swap	0.170	0.180	0.176	0.199	17.1 %

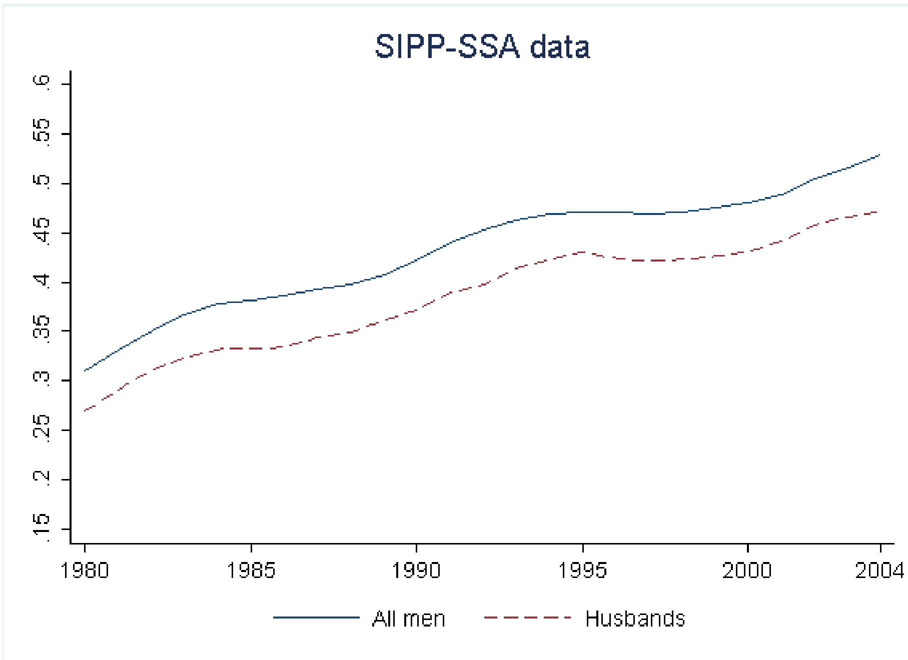
Table 4: Permanent variance of earnings, more educated household heads

	1980	1990	2000/ 2001	2004/ 2005	%Δ (2004/2005 - 1980)
			SIPP-SSA		
Men	0.280	0.369	0.430	0.476	70.0 %
Husbands	0.226	0.312	0.379	0.419	85.4 %
Couples	0.174	0.215	0.264	0.283	62.6 %
Couples, cond. swap	0.199	0.234	0.291	0.307	54.3 %
Couples, uncond. swap	0.190	0.236	0.281	0.302	58.9 %
			PSID		
Men	0.160	0.248	0.322	0.332	107.5 %
Husbands	0.143	0.195	0.287	0.295	106.3 %
Couples	0.136	0.149	0.195	0.222	63.2 %
Couples, cond. swap	0.142	0.166	0.223	0.236	66.2 %
Couples, uncond. swap	0.140	0.170	0.223	0.234	67.1 %

Table 5: Gini coefficients

	1980	1990	2000/ 2001	2004/ 2005	Δ (2004/2005 - 1980), %
			SIPP-SSA		
Men	0.258	0.306	0.338	0.348	34.9 %
Husbands	0.239	0.283	0.317	0.329	37.7 %
Couples	0.240	0.262	0.287	0.295	22.9 %
Couples, cond. swap	0.249	0.268	0.294	0.303	21.7 %
Couples, uncond. swap	0.244	0.258	0.281	0.290	18.9 %
			PSID		
Men	0.228	0.278	0.307	0.320	40.4 %
Husbands	0.222	0.261	0.289	0.300	35.1 %
Couples	0.219	0.243	0.259	0.273	24.7 %
Couples, cond. swap	0.218	0.248	0.262	0.273	25.2 %
Couples, uncond. swap	0.216	0.237	0.252	0.264	22.2 %

Figure 1: Permanent variance for men, 5-year window



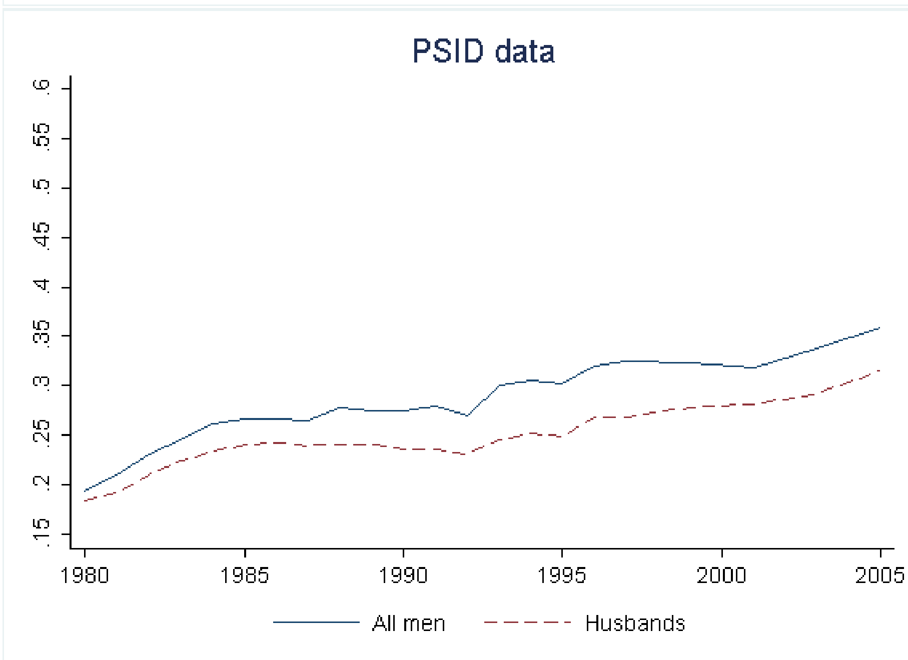


Figure 2: Transitory variance for men, 5-year window

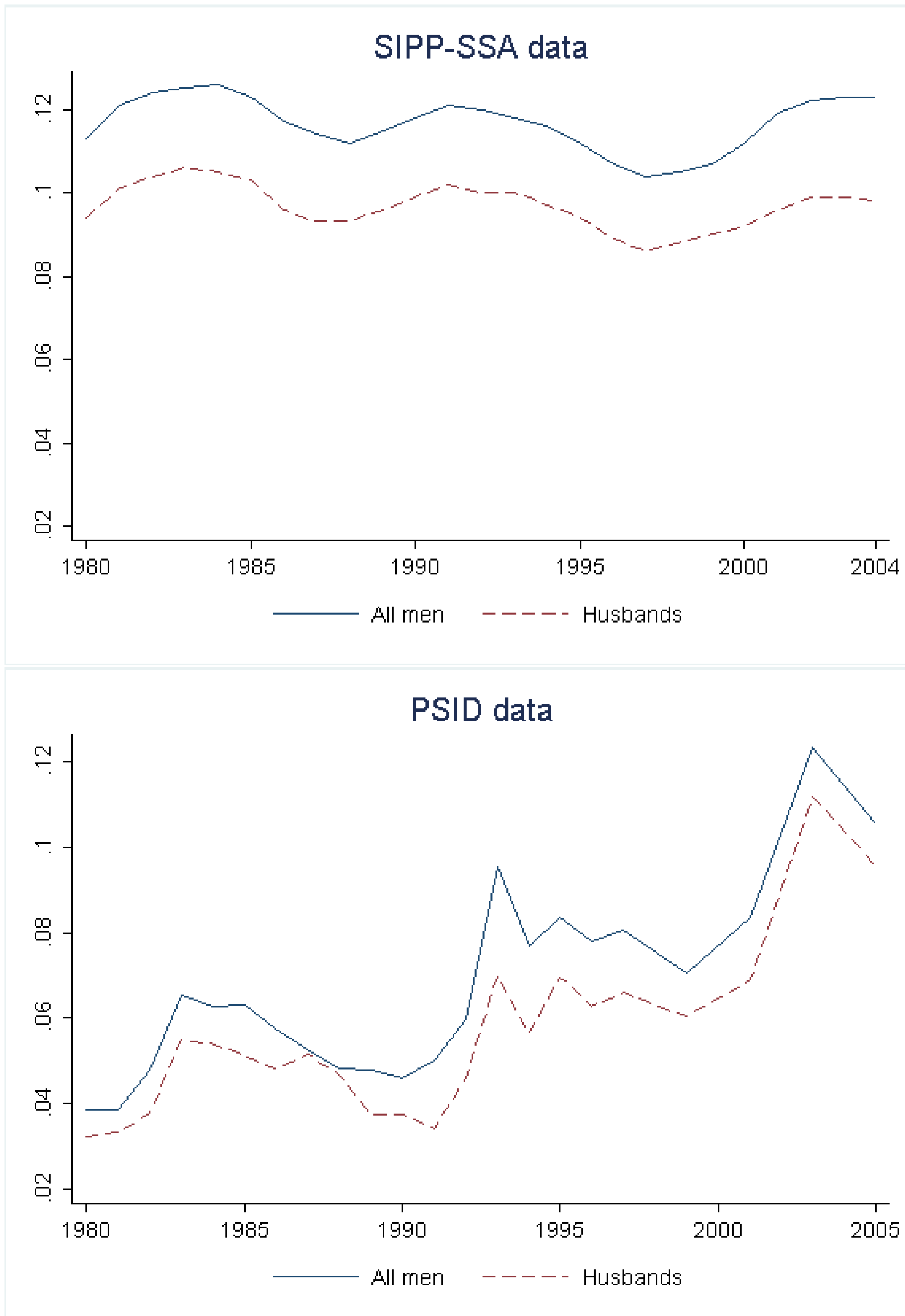


Figure 3: Permanent variance for couples, 5-year window

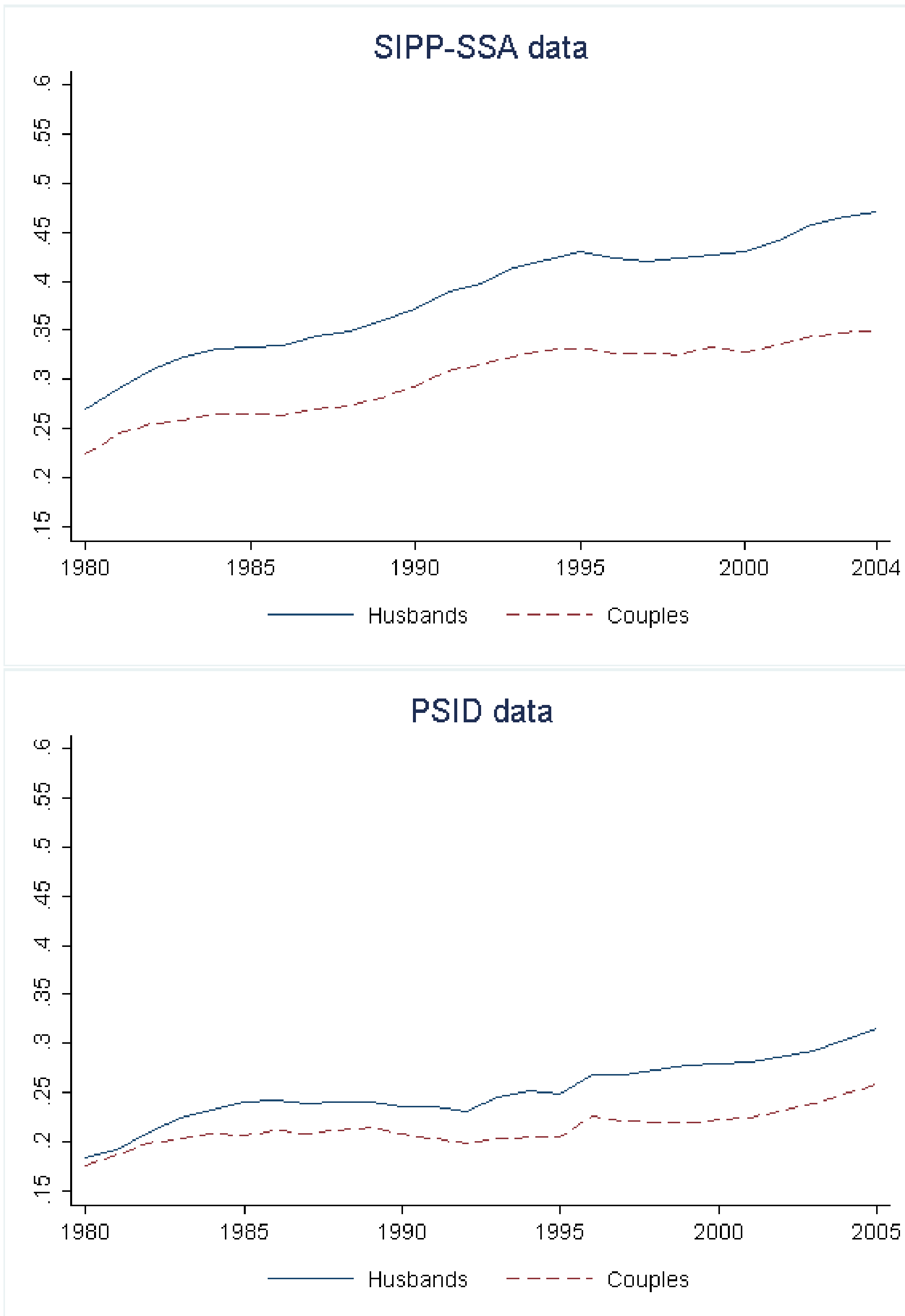


Figure 4: Transitory variance for couples, 5-year window

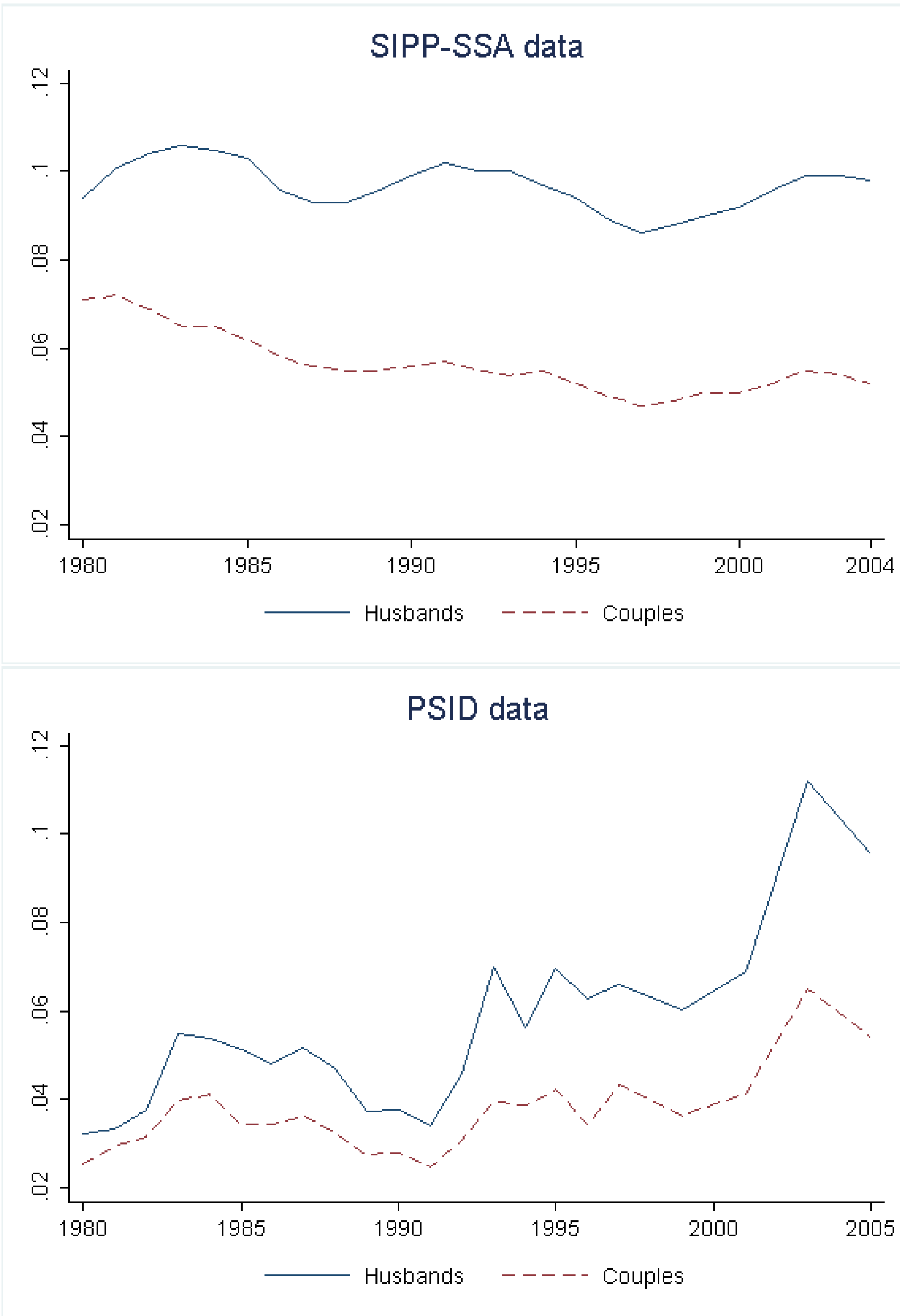


Figure 5: Permanent variance for actual and rematched couples, 5-year window

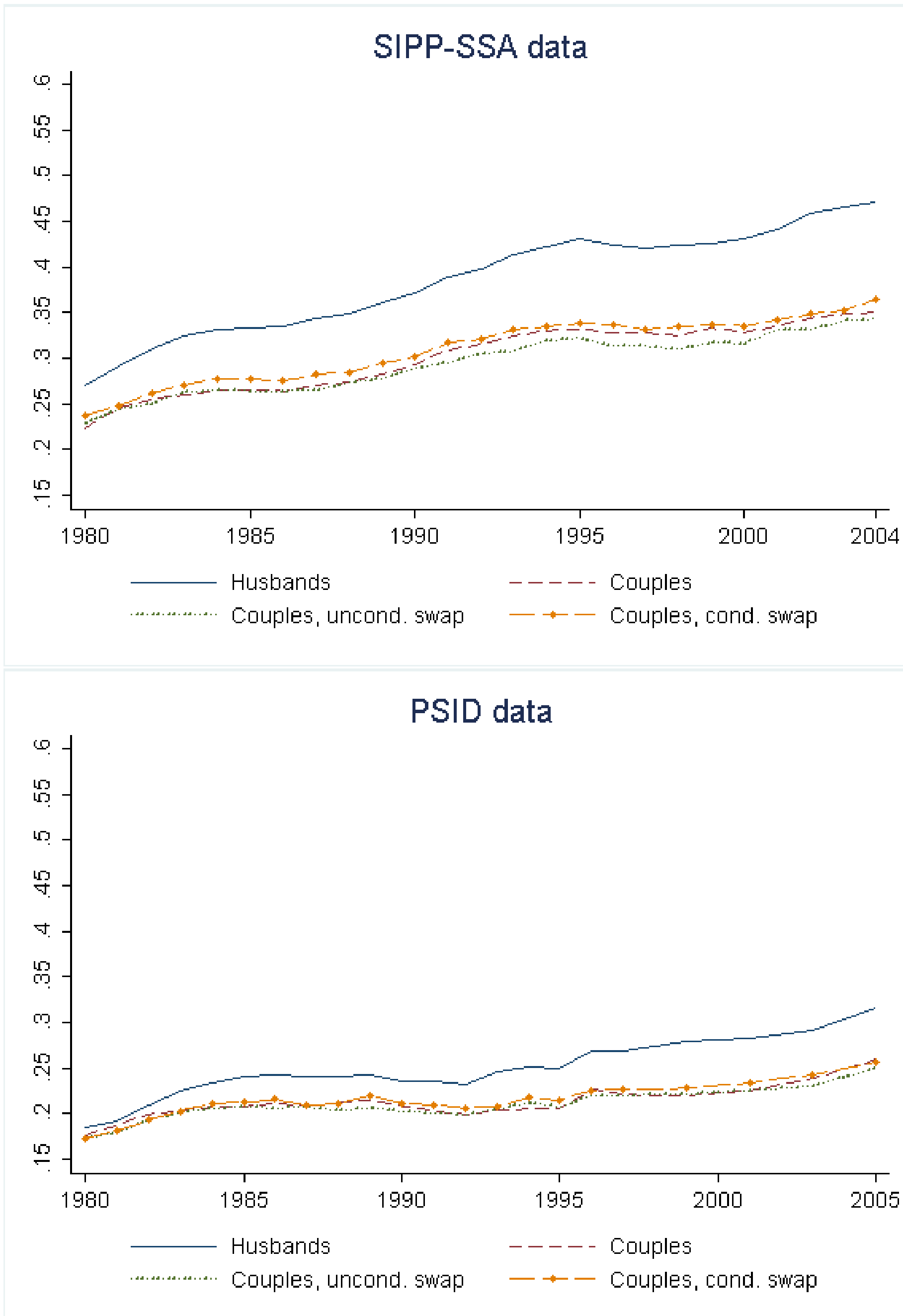


Figure 6: Correlation, permanent incomes of head and wife

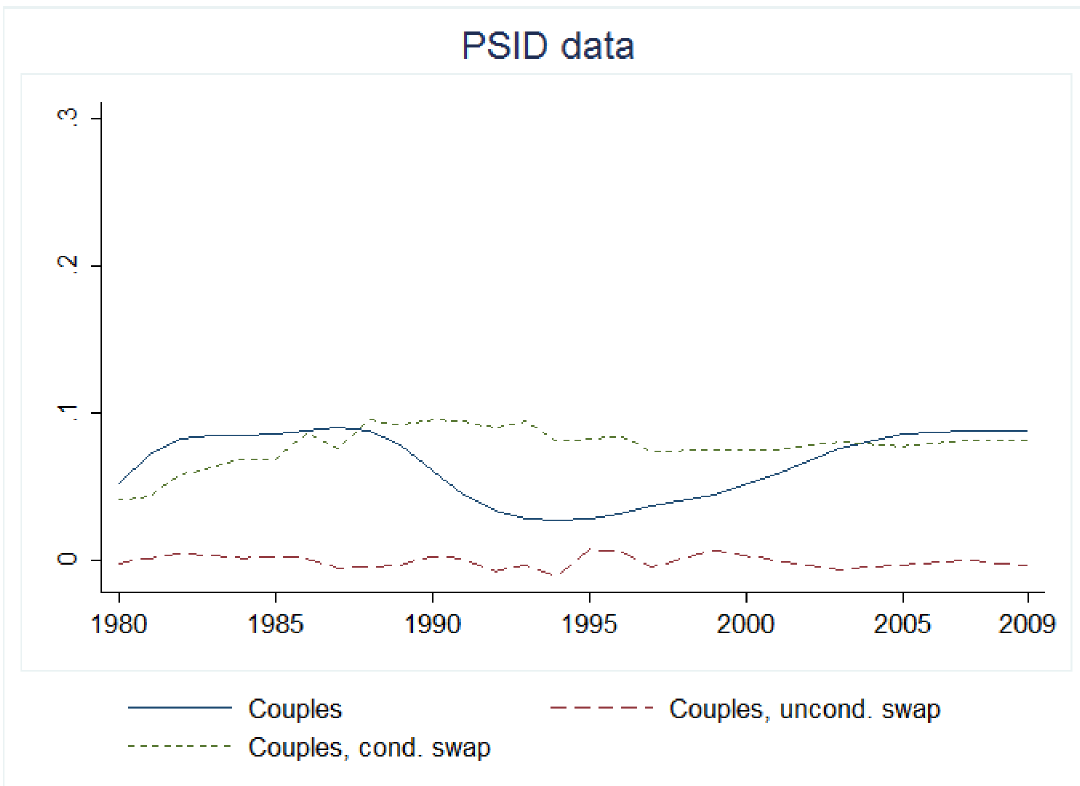
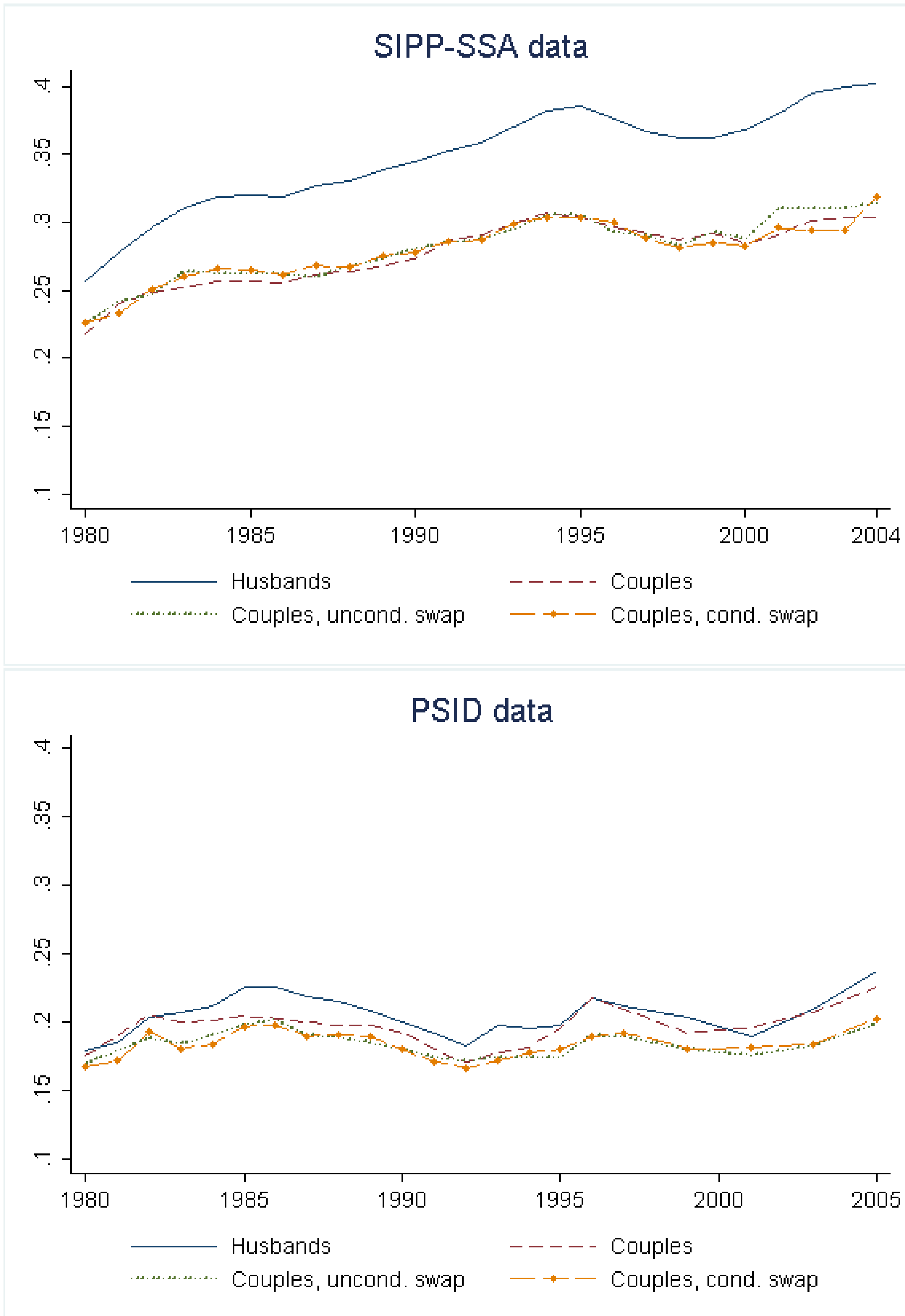
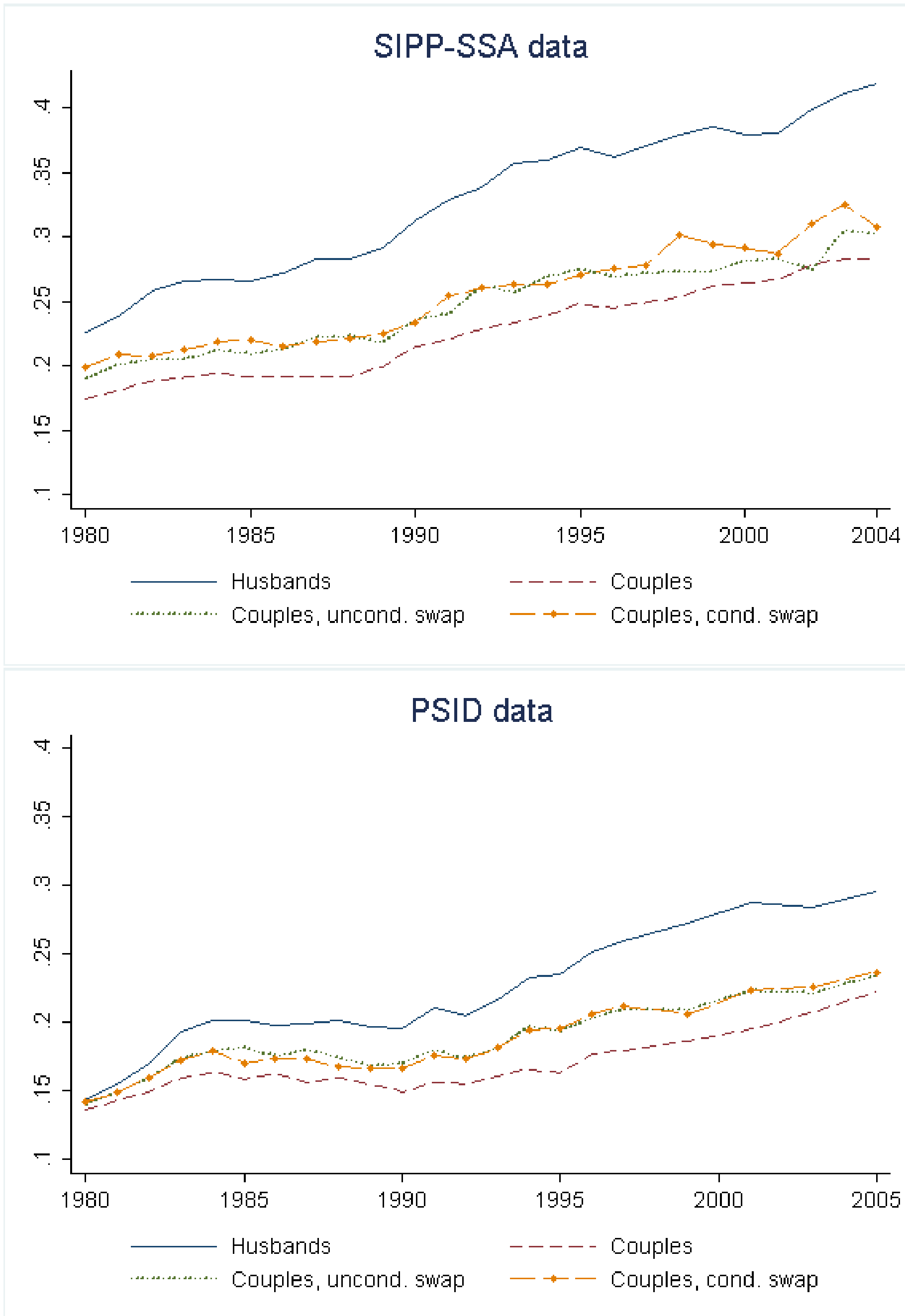


Figure 7: Permanent variance, 5-year window. Less educated heads



Notes: In SIPP-SSA data, less educated are the heads whose schooling is less than 16 years; in the PSID, less educated are the heads whose schooling is less than or equal to 12 years.

Figure 8: Permanent variance, 5-year window. More educated heads



Notes: In SIPP-SSA data, more educated are the heads whose schooling is more than or equal to 16 years; in the PSID, more educated are the heads whose schooling is more than 12 years.

Figure 9: Transitory variance, 5-year window

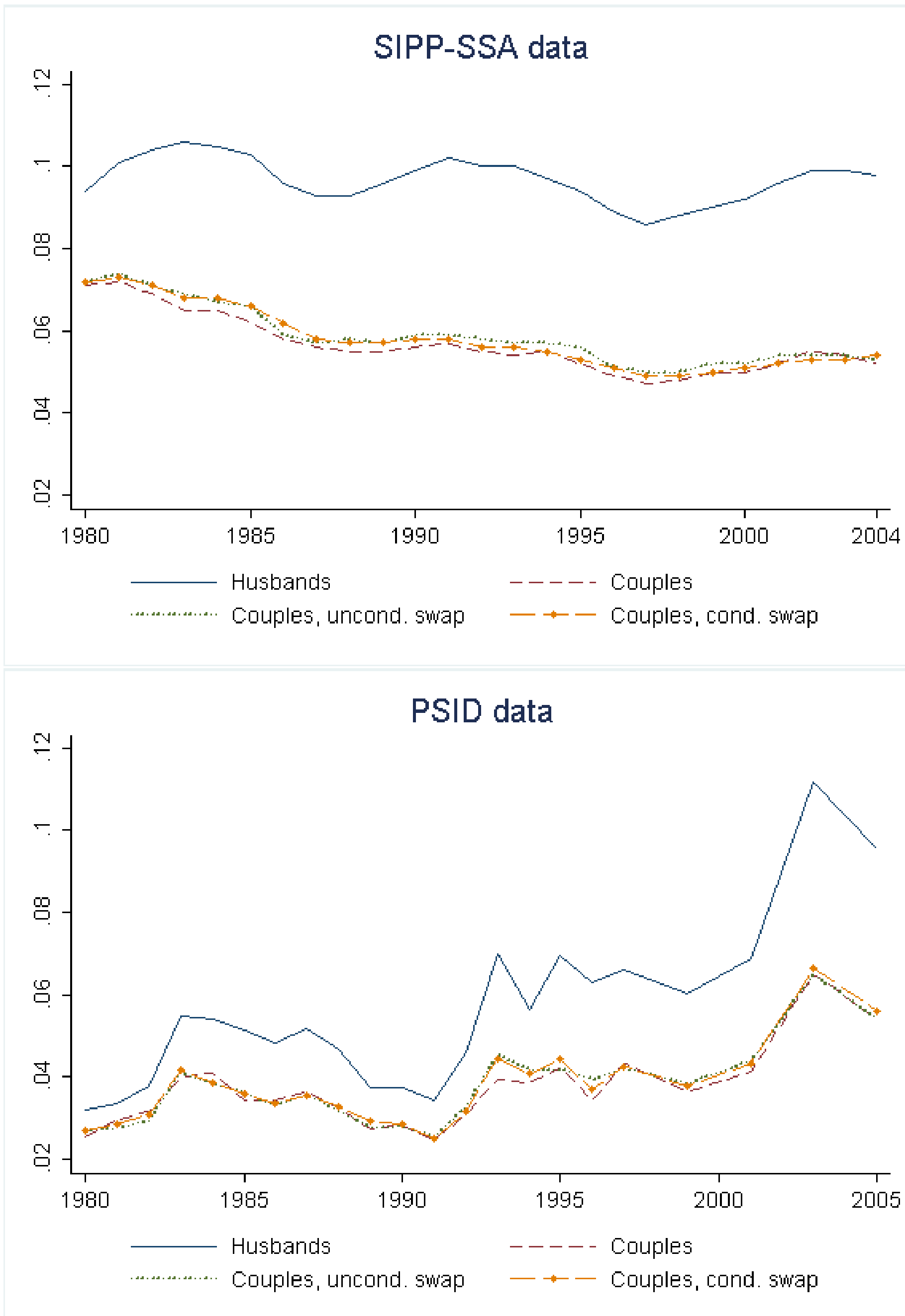


Figure 10: Gini coefficients for actual and rematched couples, 5-year window

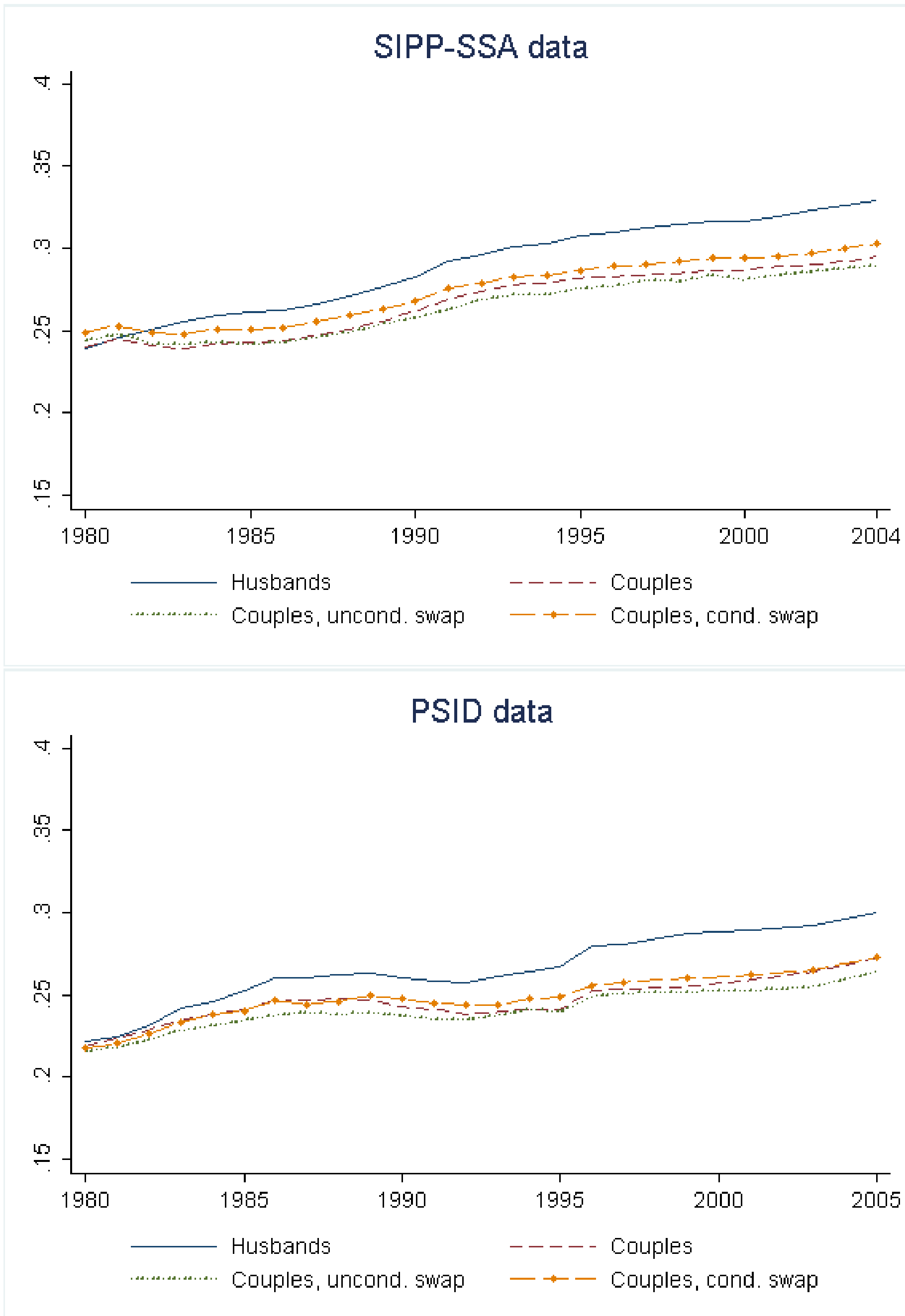


Figure 11: Gini coefficients and permanent variance for actual and re-matched couples, 5-year window, Hyslop's selection

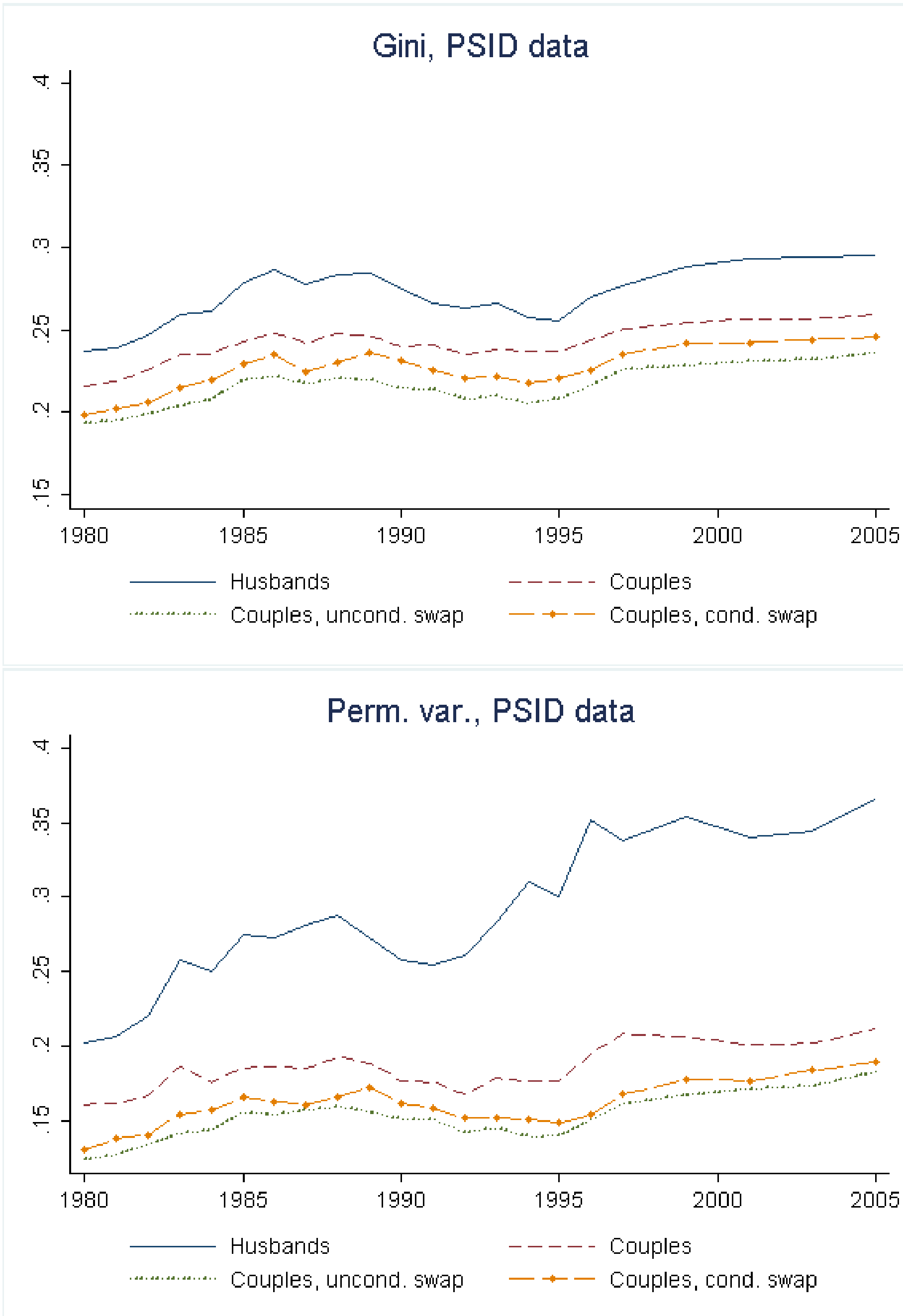


FIGURE 12: GINI COEFFICIENTS AND PERMANENT VARIANCE FOR ACTUAL AND RE-MATCHED COUPLES, 5-YEAR WINDOW, GREENWOOD ET AL.'S SELECTION

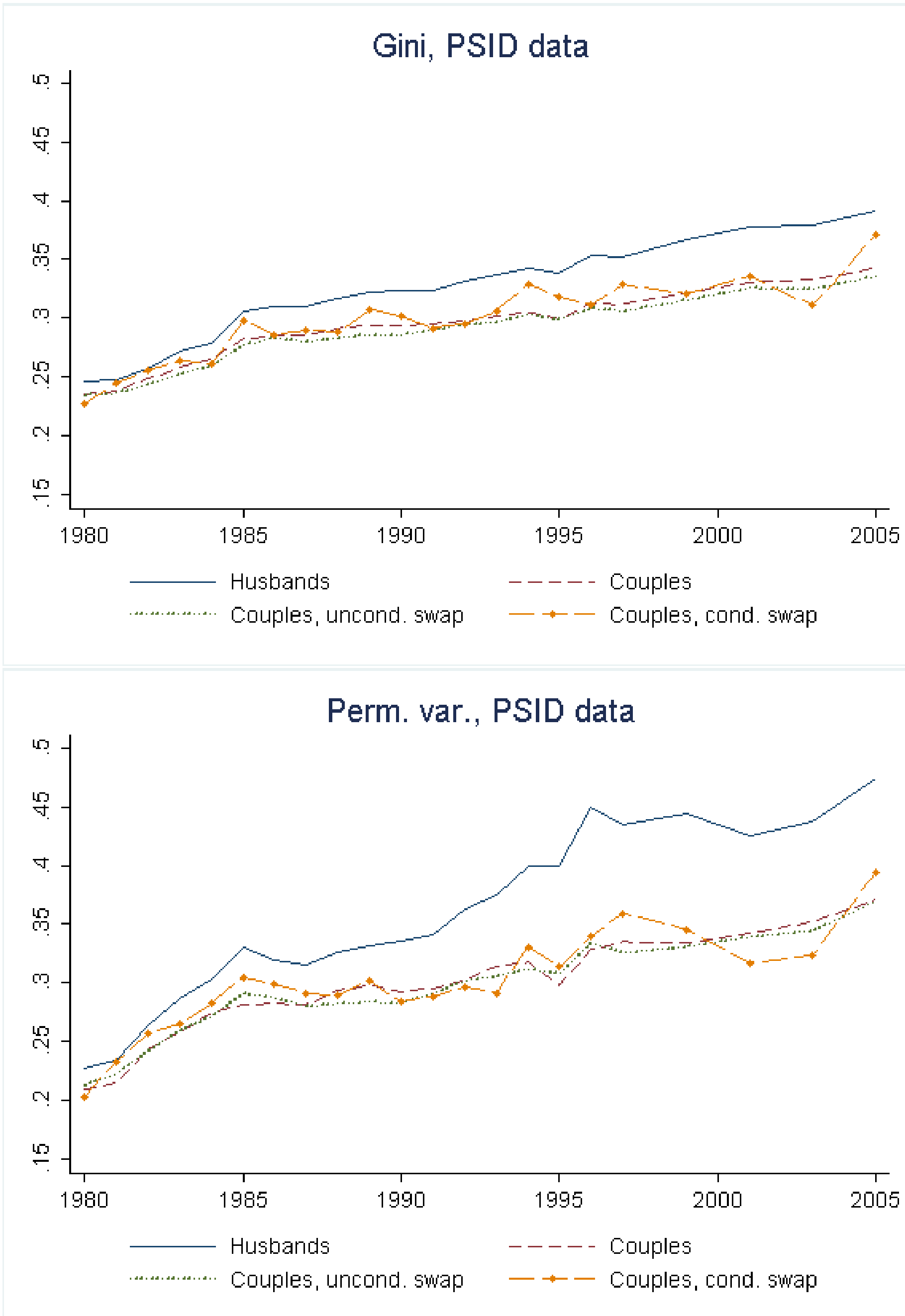


Figure 13: Correlation, permanent incomes of head and wife