Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967-2006*

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Abstract

We conduct a systematic study of cross-sectional inequality in the United States over the period 1967-2006. Our empirical analysis integrates three widely-used micro data sources: the March Current Population Survey (CPS), the Panel Study of Income Dynamics (PSID), and the Consumer Expenditure Survey (CEX). We follow the mapping suggested by the household budget constraint from dispersion in individual wages to individual earnings, from individual to household earnings, and from household earnings to disposable income and ultimately consumption. Our main message is that both levels and trends in economic inequality depend crucially on the variable of analysis. Thus it is critical to understand how different dimensions of inequality are related via endogenous choices and institutions. Substantially, we find a continuous and sizable increase in wage inequality over the sample period. Changes in the distribution of hours sharpen the rise in inequality in the first half of the sample, but mitigate rising inequality in the post 1982 period. Taxes and transfers compress the level of inequality, especially at the bottom of the distribution, but have little overall effect on the trend. Finally, consumption data suggest that access to financial markets has reduced both the level and growth of economic inequality.

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1 Introduction

The evolution of economic inequality in the United States has been extensively studied. One branch of the literature focuses on the wages of full-time men, using data from the March Current Population Survey (CPS). This work aims to describe the evolution of dispersion in productivity and skills, and to identify its macroeconomic sources, such as technology, trade, or institutions (see Katz and Autor, 1999, for a survey). Another branch of the literature focuses on labor supply, studying, for example, how changes in unemployment or female participation affect measures of economic inequality. Other authors have emphasized that whether increasing dispersion is permanent or transitory in nature has important implications for policy and welfare, and have investigated income dynamics using the longitudinal dimension of the Panel Study of Income Dynamics (PSID) (e.g. Gottschalk and Moffitt, 1994). This shift from the sources of rising inequality to its welfare implications continues with the investigation, based on the Consumer Expenditure Survey (CEX), of the trend in inequality in household consumption, a more direct measure of well-being (e.g., Cutler and Katz, 1991).

Even though much has been learned from these studies, the literature lacks a systematic analysis of US cross-sectional inequality that jointly examines all the key measures of economic inequality (wages, hours, income and consumption) based on comparable samples from the three most widely-used different data sets (CPS, CEX, PSID). Such an effort would provide a more comprehensive view of inequality in the US, and shed light on how different dimensions of inequality are related via endogenous choices, markets and institutions.

In this paper, we try to fill this gap. To undertake this task, it is natural to use the household budget constraint as a key organizing device. Therefore, rather than focusing on a specific measure of economic inequality, we begin with changes in the structure of individual wages as our most primitive measure of inequality, and from there take a series of steps to contrast inequality in individual wages to that in individual earnings, household earnings, pre-government income, disposable income, and, ultimately, consumption. Along the way, we evaluate the impact on measured inequality of individual labor supply, household income pooling, private transfers and asset income, government redistribution, and household net saving.

Our empirical analysis is beneficial to two strands of research. The first is the quantitative theoretical research aimed at understanding how individual-level risk affects the distribution of economic outcomes (e.g., Imrohoroglu, 1989; Huggett, 1993; Aiyagari, 1994; Rios-Rull, 1996;

Krueger and Perri, 2006, Heathcote et al., 2008). Our study is intended provide some new facts and to improve and sharpen the characterization of old facts, so that models of this type can be used with more confidence to understand the relationship between risk and outcomes.

The second line of research is the one aiming at understanding the distributional impact of macroeconomic changes or shocks (e.g., Krusell and Smith, 1998, Castaneda, Diaz-Gimenez and Rios-Rull, 2003, Storesletten Telmer and Yaron, 2004a). By characterizing the evolution of various distributions over a long period of time, our paper paints a more complete picture of the impact of macro changes on various segments of the population.

We now briefly summarize our key substantive findings.

Looking at individual wages, inequality rises steadily since the early 1970s for men, and since the early 1980s for women. However, dispersion in hourly wages increases mostly at the bottom the wage distribution in the 1970s, throughout the distribution in the 1980s, and at the top after 1990.

Shifting the focus from wage to earnings inequality, we detect a strikingly important role for labor supply. First, the variance of log male earnings increased much more rapidly than the variance of log male wages until the mid 1980s, but much more slowly thereafter. The reason is that relative hours worked for low-skilled men declined in the 1970s, exacerbating earnings inequality at the bottom, but recovered in the late 1980s and 1990s. Second, household earnings inequality increased less than earnings inequality for the main earner in the household. This is especially true at the top of the distribution, while at the bottom the equalizing effect of spousal labor supply is limited by the prevalence of single households. Third, the age-profile for wage inequality is concave, while that for household earnings inequality is convex. This difference is due to the age-profile of hours dispersion.

As we progress from household earnings to household income, we determine that taxes and public transfers compress household income inequality dramatically, and were an important buffer against rising earnings inequality in the 1970s and early 1980s. Since then, however, the inequality-reducing effect of government has diminished.

The final step in tracing out the household budget constraint is from disposable income to consumption. The gap between the two is informative about the smoothing role of borrowing/saving and financial markets in general. We examine this key relationship from three different viewpoints. First, in the time series, we uncover that cross-sectional inequality in non-durable consumption increases by less than half as much as inequality in disposable income.

Second, we find an analogous result in the life-cycle dimension: only a fraction of age-increase in within cohort dispersion in income translates into dispersion in consumption. Third, by exploiting the longitudinal dimension of the PSID, we can distinguish the relative importance of permanent and transitory shocks: the former are more likely to pass through to consumption, the latter are more easily insurable. Here, we focus on the dynamics of "residual" wages, which most closely reflect idiosyncratic labor market risk. We detect a rise in the permanent variance in the decade 1975-1985, precisely the period when cross-sectional consumption inequality rises the most.

Finally, when we focus on the dynamics of inequality at higher frequencies, we find that cyclical fluctuations in CPS per-capita income are much larger than in NIPA personal income. Thus, viewed through the lens of microdata, business cycles, are more dramatic events. In particular, household earnings at lower percentiles of the income distribution decline very rapidly in recessions, such that recessions are times when earnings inequality widens sharply. Once again, since we do not find similar dynamics for individual wages, we conclude that the root of such large fluctuations in earnings is labor supply – unemployment especially.

Our paper contains two more methodological contributions.

The first is to check whether the CPS, CEX and PSID tell a consistent story with respect to various measures of cross-sectional dispersion. We find that, with the exception of two discrepancies that we discuss in the paper, they align closely with respect to wages, hours, earnings, and disposable income. This is reassuring, since it means that researchers can estimate individual income dynamics from the PSID, or measure consumption inequality in the CEX, and safely make comparisons to cross-sectional moments from the much larger CPS sample.

The second contribution is to show that a standard permanent-transitory model for individual wage dynamics appears mis-specified, since it cannot jointly replicate cross-sectional moments for wages in levels, and corresponding moments for wages in first-differences.

The rest of the paper is organized as follows. Section 2 describes the three data sources: the CPS, the PSID, and the CEX. Section 3 compares measures of per-capita income and consumption in the NIPA to those constructed from the surveys. Section 4 describes the trends of US cross-sectional inequality over time. Section 5 focuses on the life-cycle dimension. Section 6 provides a detailed comparison of several measures of inequality across the three data sets. Section 7 exploits the panel dimension of PSID to estimate the transitory and the permanent components of individual wage dynamics. Section 8 concludes. Many details of the empirical analysis are omitted from the main text and collected in the Appendix, to which we will refer throughout the paper.

2 Three data sets

In this section, we briefly describe our three data sets: the CPS, the PSID and the CEX. The Appendix contains more detail on each survey, precise definitions of the variables we use, and a discussion of how we construct our baseline samples.

2.1 CPS

The CPS is the source of official US government statistics on employment and unemployment, and is designed to be representative of the civilian non-institutional population. The Annual Social and Economic Supplement (ASEC) formerly known as the Annual Demographic Survey applies to the sample surveyed in March, and extends the set of demographic and labor force questions asked in all months to include detailed questions on income. For the ASEC supplement, the basic CPS monthly sample of around 60,000 households is extended to include an additional 4,500 hispanic households (since 1976) and, more importantly, an additional 34,500 households (since 2002) as part of an effort to improve estimates of children's health insurance coverage: this sample expansion is known as the SCHIP sample.

The basic unit of observation is a housing unit, so we report CPS statistics on inequality at the level of the household (rather than at the level of the family). The March CPS contains detailed demographic data for each household member and labor force and income information for each household member aged 15 or older. Labor force and income information correspond to the previous year. We ignore the limited panel dimension to the CPS, and treat it as a pure cross-section. We use the March supplement weights to produce our estimates.

2.2 PSID

The Panel Study of Income Dynamics (PSID) is a longitudinal study of a sample of US individuals (men, women, and children) and the family units in which they reside. The PSID was originally designed to study the dynamics of income and poverty. For this purpose, the original 1968 sample was drawn from two independent sub-samples: an over-sample of roughly 2,000 poor families selected from the Survey of Economic Opportunities (SEO), and a nationallyrepresentative sample of roughly 3,000 families from the 48 contiguous US states designed by the Survey Research Center (SRC) at University of Michigan.

Since 1968, the PSID has interviewed individuals from families in the initial samples, whether or not they were living in the same dwelling or with the same people. Adults have been followed as they have grown older, and children have been observed as they have advanced into adulthood, forming family units of their own (the "split-offs"). Survey waves are annual from 1968 to 1997, and biennial since then. The PSID is the longest-running representative household panel for the United States.

The PSID data files provide a wide variety of information about both families and individuals. The focus of the data is economic and demographic, with substantial detail on income sources and amounts, employment status and history, family composition changes, and residential location. While some information is collected about all individuals in the family unit, the greatest level of detail is ascertained for the primary adults in the family unit, i.e. the head (the husband in a married couple) and the spouse, when present.

We base our empirical analysis on the "SRC sample". We use all the yearly surveys (1967-1996) and the biennial surveys for 1999, 2001 and 2003. Since the SRC sample was initially representative of the US population, the PSID does not provide weights for this sample. The primary concern about the representativeness of this sample is that it does not capture the post-1968 inflow of immigrants to the United States. We return to this point in Section 6.

2.3 CEX

The Consumer Expenditure Survey (CEX) consists of two separate surveys, the quarterly Interview Survey and the Diary Survey, both collected for the Bureau of Labor Statistics by the Census Bureau. It is the only US dataset that provides detailed information about household consumption expenditures. The diary survey focuses only on expenditures on small, frequently-purchased items (such as food, beverages and personal care items), while the interview survey aims to provide information on up to 95% of the typical household's consumption expenditures. Thus in this study we will focus only on the interview survey (see Attanasio, Battistin and Ichimura 2007 for a study that uses both the diary and the interview surveys).

The CEX Interview Survey is a rotating panel of households that are selected to be representative of the US population. It started in 1960, but continuous data are available only from the first quarter of 1980 until the first quarter of 2007, so we focus on this period. Each quarter the survey reports, for the cross section of households interviewed, detailed demographic characteristics for all household members, detailed information on consumption expenditures for the three month period preceding the interview, and information on income, hours worked and taxes paid over a yearly period.[1] Each household is interviewed for a maximum of four consecutive quarters, but a large fraction (over 60%) of households is interviewed less than four times. For all the statistics computed in this paper, the universe of records for analysis in the CEX is constituted by all household/quarter observations that satisfy the sample restrictions discussed below.

2.4 Comparability of data sets

The three surveys are similar enough to make comparison across datasets meaningful and appropriate. However, definitions of some key variables are different, which often explains divergence in levels or trends of sample statistics.

The unit of analysis in the CPS and the CEX is the household– all persons, related or unrelated, living together in a dwelling unit –while in the PSID it is the "family unit"– persons living together who are usually related by blood, marriage, or adoption. In addition, prior to 1975 and post 1994, labor income and hours worked are not reported in the PSID for household members who are not heads or spouses. Thus all our labor market statistics for the PSID refer only to heads and spouses, whereas in the CPS and the CEX we also include other adult household members.

Individual labor income is defined in all three surveys as the sum of all income from wages, salaries, commissions, bonuses, and overtime, and the labor part of self-employment income. The CPS imputes values for missing income data, while the PSID and the CEX do not. In CPS and CEX data we allocate 2/3 of self-employment income to labor and 1/3 to capital, while the reported PSID income data builds in a 50-50 split. Only in the CEX is it possible to impute rents from owner-occupied housing across the entire sample period, so for the sake of consistent measurement we exclude imputed rents throughout.

The calculation of taxes differs across data sets. The PSID includes a variable for household income taxes only up until 1991. Rather than using this variable, we use the NBER's TAXSIM program to calculate an estimate of household federal and state income taxes that is comparable

[1] See the appendix for more details on the issue that income and consumption measures refer to periods that are never of the same length and that are, in some cases, non-overlapping.

across all years in the sample. The CPS contains imputed values for federal and state income taxes, social security payroll taxes, and the earned-income tax credit for the 1979-2004 income years. The CEX asks each household member in the second and fifth interview to report taxes paid (federal, state and local) in the previous year.

Top-coding affects very few observations in the PSID, but is a more serious concern in the CPS and the CEX. In all data sets, we forecast mean values for top-coded observations by extrapolating a Pareto density fitted to the non-top-coded upper end of the observed distribution. We apply this procedure separately to each component of income in each year (see the Appendix for more details.)

2.5 Sample selection

In each of our three datasets, we construct three different samples, which we label samples A, B, and C. Table 1 shows the number of records in each dataset that were lost at each stage of the selection process.

Sample A is the most inclusive, and is essentially a cleaned version of the raw data. We only drop records if 1) there is no information on age for either the head or the spouse, 2) if either the head or spouse has positive labor income but zero annual hours (zero weeks worked in the CPS), and 3) if either the head or wife has an hourly wage less than half the corresponding Federal minimum wage in that year. In the CEX, we drop households which report implausible consumption expenditures (in the PSID, we drop these households only when computing moments involving consumption). In order to reduce measurement error in income, we also exclude CEX households flagged as "incomplete income reporters" (see Nelson, 1996). Sample A is designed to be representative of the entire US population, and is used for Figures 1-3, where we compare per-capita means from micro-data to NIPA aggregates.

Sample B is further restricted by dropping a household from sample A if no household member is of working age, which we define as between the ages of 25 and 60 (in the PSID we drop households if neither the head nor the spouse falls in this age range). The household head is the oldest working age male, as long as there is at least one working-age male in the household - otherwise the head is the oldest working-age female. Sample B is our household-level sample and is used for Figures 8-16, where we study household-level inequality.

Sample C instead is an individual-level sample. To obtain it, we first select all individuals aged 25-60 who belong to households in sample B. From this group we then select those who work at least 260 hours in the year. Sample C is used for Figures 4-7 and 14-18.

Table 2 reports statistics on some key demographic characteristics for sample B. The table indicates broad agreement, both in terms of levels and with respect to demographic trends over time. One exception is that the fraction of white males is declining over time in the CPS and the CEX, but stable in the PSID. This reflects higher attrition for non-whites in the PSID coupled with the fact that the PSID misses disproportionately non-white recent immigrants. In addition, a significantly larger fraction of households (families) in the PSID contain married couples, suggesting that the PSID under-samples non-traditional households.

2.6 Outline

We begin by comparing the evolution of average household earnings, income and consumption in our micro data to the official National Income and Product Accounts (NIPA), over the period 1967-2005. Next, we compare trends in average wages and hours worked across the CPS, PSID and CEX. We then move to analyzing time trends in individual-level inequality statistics, and in household-level dispersion measures, for various definitions of income and for consumption. Next, we study the evolution of inequality over the life cycle. Finally, we estimate stochastic processes for individual wages, allowing for time variation in the parameters.

In what follows, we express all income and expenditure variables in year 2000 dollars. The price deflator used is the Bureau of Labor Statistics CPI-U series, all items. Our equivalence scale is based on the OECD scale, and assigns a value of 1.0 to the first adult, a weight of 0.7 to each additional adult, and a weight of 0.5 to each child.[2]

3 Means

Labor income The income definition that is conceptually most similar across the CPS and the NIPA is labor income. CPS labor income includes total income from wage and salary, but it excludes self-employment income. The corresponding NIPA labor income measure is "wage and salary disbursements" (NIPA Table 2.1, line).[3]

[2]In the PSID, a child is a family member age 17 or younger. In the CPS and the CEX we define a child as age 16 or younger. The original OECD definition is 13 or younger.

[3]Two minor differences, however, are worth noting (Ruser, Pilot and Nelson, 2004). The first is that the BEA classifies as dividends all S corporation profits distributed to shareholders, while the Census treats these profits as wage and salary income if the recipients are shareholder-employees. The second is that the BEA (but not the CPS) makes an upwards adjustment for wage and salary income earned in the underground economy

The top panel of Figure 1 compares labor income in the CPS to the NIPA. Both series are per capita, real and logged.[4] Labor income aligns remarkably well, in terms of levels, trends, and business cycle fluctuations. On average across the 1967-2005 period, the CPS statistic exceeds its NIPA counterpart by 0.27 percent. The average absolute discrepancy is 1.1 percent. In the early 1990s, CPS labor income rises somewhat more rapidly than in the NIPA, a finding previously noted by Roemer (2002). Conversely, in the early 2000s the decline in CPS labor income is less evident than in the NIPA.[5]

Pre-tax income The CPS measure of pre-tax income includes labor income, self-employment income, net financial income, and private and public transfers. This is our version of the "money income" concept constructed by the Census. Labor income alone accounts for fully three quarters of total CPS pre-tax income. The corresponding NIPA income measure is "personal income" (NIPA Table 2.1, line 1).

On average across the sample period, CPS income falls 21 percent short of NIPA income. In light of the previous discussion, this gap must be attributed to income other than labor income. The NIPA-CPS gap widens over time, by around 10 percentage points of NIPA income. There are several reasons for this gap.

First, there is a downward bias in the CPS income series arising from internal censoring of high income values: our treatment of externally top-coded observations described in the Appendix should partially correct for this problem.[6]

Second, there is an important conceptual difference between survey-based income measures and NIPA income. The surveys record cash income received directly by individuals, while the NIPA records cash and in-kind income collected on behalf of individuals.[7] The "by" versus "on behalf of" distinction means that dividends, interest and rents received on behalf of individuals

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from legal but "off the books" activities.

[4]The US population estimate is from NIPA Table 7.1, line 16.

[5]The reliability of CPS labor income reporting is confirmed by Roemer (2002), who matches individuals in the March CPS to detailed earnings records from the Social Security Administration (DER). He finds that part-year, part-time workers have underestimated March CPS wages (CPS/DER ratio around 90 percent), but that for all other groups wages align very closely.

[6]At the start of the sample period our CPS estimate for per capita income exceeds the official Census series by over 7 percent. This gap narrows to less than 1 percent towards the end of the period as the Census increased internal censoring points. For example between 1992 and 1993, when the censoring point for earnings on the primary job rose from \$300,000 to \$1m, the gap narrows from 5.3 percent to 2.5 percent.

[7]Table 1 in Ruser et. al. (2004) provides a careful and detailed account of the differences. They find that in 2001, 64 percent of the \$2.23 trillion gap between aggregate NIPA personal income and aggregate CPS money income can be accounted for by differences in income concepts (see also Roemer, 2000).

by pension plans, nonprofits and fiduciaries is in NIPA income but not survey income. The "cash" versus "cash and in-kind" distinction means that employer contributions for employee pension and health insurance funds are in NIPA income, but not survey income. Employer contributions of this type rose from 4.3 percent of NIPA personal income in 1967 to 9.0 percent in 2005, explaining a large part of the widening NIPA-CPS gap. Similarly the NIPA includes (but the surveys exclude) the imputed rental value of owner-occupied housing and in-kind transfers such as Medicare, Medicaid and food stamps.[8]

In addition to these conceptual differences, an additional gap between the NIPA and survey-based estimates arises because survey respondents tend to under-report a range of types of income, while the BEA attempts in a variety of ways to make upward adjustments for components of income that are self-reported.[9]

Cyclical fluctuations The CPS mirrors the business cycle fluctuations evident in the NIPA income series. However, cyclical fluctuations appear larger in the CPS than in the NIPA. From peak to trough, percentage real income declines in the CPS (NIPA) for the recessions in the mid 70s, early 80s, early 90s and early 00s are 3.9 (2.2), 6.6 (2.9), 5.1 (2.3) and 2.2 (1.3). While recession declines in per-capita pre-tax income are roughly twice as large in the CPS, declines in wages and salary are very similar in magnitude. Thus the difference in business cycle dynamics must be attributed to unearned components of income. Future work should more precisely characterize the reason for this discrepancy, to understand whether it reflects differences in the income concepts used by the Census and the BEA, or whether it is more of a measurement issue. In the meantime, it is important to be aware that macro and micro data paint different pictures for the size of cyclical fluctuations.

Wages and hours Figure 2 plots average wages and hours over the sample period.[10] Wages are computed as annual earnings divided by annual hours, where earnings includes labor

[8] In the other direction, the surveys include but the NIPA excludes personal contributions for social insurance, income from private pension and annuities plans, income from government employee retirement plans, and income from interpersonal transfers, such as child support.

[9] For example, the proprietors income adjustment is based on evidence that proprietors' actual income in 1999 was more than double levels reported on tax returns. Ruser et al. (2004) note that it is likely that respondents who underreport to the IRS also underreport in voluntary surveys. Comparing various components of income across the CPS and other independent estimates, Ruser et al. note that under-reporting in the CPS seems to be important for private and government retirement income, interest and dividend income, and social security income.

[10] The estimates of average hours in Figure 2 are based on all 25-60 year-old individuals in Sample B, including those working zero hours. Average wages apply to Sample C, which excludes individuals working less than 260 hours in the year.

income plus two thirds of self-employment income.[11]

The average real wage for women rises by 36 percent over the period. In contrast, the corresponding increase for men is only 14 percent, with real wage declines in the 1970s and 1980s recouped in the 1990s. Business cycle fluctuations are evident in both average wage series.

Average male hours decline in the 1970s and are broadly stable thereafter.[12] In contrast, female market hours increase dramatically in the 1970s and 1980s, as female wages rise relative to male wages. This growth in female participation slows in the 1990s, at the same time that male wage growth picks up again.

How can stagnant real hourly wages and hours worked for male workers (Figure 2) be reconciled with rising per capita labor income (Figure 1)? The answer lies in women's labor market outcomes. Over the sample period, two thirds of the growth in labor income per capita is attributable to growth in female labor income per capita. Rising female labor income, in turn, reflects both rising average hours for women, and rising average labor income per hour. Of the two, the former is more important: hours worked per woman increase by 92 percent over the sample period, real female labor income per hour rises by 30 percent. Most of the increase in female hours is on the extensive margin.[13]

Consumption Figure 3 reports various measures of per-capita consumption for the CEX and the PSID, and contrasts them with comparable aggregates for personal consumption expenditures from the NIPA. The top-left panel reports aggregate expenditure on food (including alcoholic beverages and food away from home). The plot confirms that food expenditures in the CEX and the PSID track each other fairly closely (see Blundell, Pistaferri and Preston, 2008, for a similar finding in the earlier part of our sample). However, the survey-based estimates are lower than NIPA food expenditure, and, more disturbingly, the gap between the two series is increasing over time. This growing discrepancy –from 20 to 60 percent– is even more marked for a broader definition of non-durable consumption (the top-right panel).[14] The bottom two

[11] Recall that prior to income year 1975, CPS information on hours - and thus wages - is not ideal because the question about weekly hours refers to hours worked last week (rather than usual weekly hours). Moreover, information about weeks worked in the previous year is available only in intervals prior to 1975. We have used information for years in which both measures of hours are available to splice together estimates for the 1967-1974 period and those for the later period.

[12] Our CPS estimates align very closely by year and age group with the decennial Census-based estimates of McGrattan and Rogerson (2004, Table 3).

[13] Hours are computed using hours worked last week, which is available throughout the sample period.

[14] The definition (in both NIPA and CEX) includes the following categories of non-durables and services:

panels show that even for expenditures on durables and housing services, there is a growing gap between expenditures measured in the CEX and in the NIPA.[15]

Some recent research investigates the large and widening gap between CEX and NIPA aggregate consumption (Slesnick, 2001; Garner et al., 2006). This work suggests that conceptual differences between the CEX and the NIPA can account for some of the discrepancy, both in terms of levels and growth rates. For example, the CEX only includes the out-of-pocket portion of medical care spending, which is a rapidly growing item in NIPA consumption. However, as Figure 3 makes clear, the growing gap between the CEX and the NIPA applies across a broad range of consumption categories, suggesting specific definitional differences are only part of the explanation.[16]

Another candidate explanation is that the CEX sample under-represents the upper tail of the income and consumption distributions, and that growth in aggregate consumption has been largely driven by these missing wealthy households. However, one would expect this type of sample bias to show up in income as well as in consumption, and it does not: CEX per-capita income tracks NIPA per-capita income well (see Section 6). In other words, CEX consumption grows slowly relative to CEX income, and not just relative to NIPA consumption.

Interestingly, survey-based aggregate consumption also fails to keep up with survey-based income and with national-accounts consumption in the UK Family Expenditure Survey (see Blundell and Etheridge, 2009, in this volume). Understanding the reasons for this discrepancy remains an important open research question.

4 Inequality over time

This section is devoted to characterizing the evolution of cross-sectional inequality in the United States in the last 40 years. We find that making general statements about inequality over this period can be misleading for two reasons. First, the specific metric for inequality matters, since measures of dispersion that emphasize the bottom of the distribution (such as the P50-P10 ratio or the variance of log) often evolve quite differently than measures that emphasize the

food, clothing, gasoline, household operation, transportation, medical care, recreation, tobacco and education.

[15]Durable consumption includes expenditures on vehicles and on furniture, while expenditure on housing services include imputed rent on owner-occupied housing plus rent paid by renters.

[16]For example, Garner et al., 2006 show that the ratio between CEX and NIPA expenditures for the specific category "Pets, toys and playground equipment", whose definition is the same in NIPA and CEX, declines from 0.71 in 1984 to 0.48 in 2002.

top of the distribution (such as the P90-P10 ratio or the Gini coefficient). Second, and more importantly, wages, earnings, income and consumption exhibit surprisingly different dynamics.

To understand why, we trace out the mapping suggested by the household budget constraint from dispersion in individual wages (reflecting inequality in endowments) to dispersion in household consumption (reflecting inequality in welfare). The steps in this mapping are from individual wages to earnings, from individual earnings to household earnings, from household earnings to disposable income, and ultimately from disposable income to consumption.

To our knowledge, this is the first paper documenting the joint evolution of all these variables in the United States using comparable samples from several surveys. The closest paper to ours, as discussed in the Introduction, are Burgess (1999) and Gottschalk and Danziger (2005) which explore the mapping from wages to pre-tax income in CPS alone. Moreover, they do not document trends in disposable income or consumption. For over-lapping variables and sample periods, our results line up well with theirs.

4.1 Individual-level inequality

Wages We begin our discussion of individual-level inequality with wages. Figure 4 displays four measures of dispersion in hourly wages by gender.[17] The variance of log hourly male wages increases throughout the period, while the variance of log female wages is relatively stable in the 1970s, but increases rapidly in the 1980s. Similar dynamics are apparent in the Gini coefficient for wages, with inequality increasing throughout the sample period, and especially in the 1980s and 1990s. Quantitatively, the overall rise in wage inequality is substantial. The variance of male wages rises by around 21 log points, and the Gini by 11 points. The corresponding figures for women are 16 and 7 log points. Eckstein and Nagypal (2004, Figure 3) report similar findings.

Turning to the percentile ratios, we uncover different trends in the top and bottom halves of the wage distribution.

The male 50th-10th percentile ratio (P50-P10) rises steadily until the late 1980s, but is quite stable thereafter. The pattern for women is similar, except that almost all of the increase in the female P50-P10 is concentrated in the 1980s. Women are paid less than men on average, and are twice as likely to be paid at or below the Federal minimum wage.[18] Thus wage compression

[17]Recall that all the individual-level statistics are computed on sample C which includes individuals aged 25-60 who work at least 260 hours per year, with wages at least half the legal Federal minimum wage.

[18]About 4 percent of women paid hourly rates reported wages at or below the prevailing Federal minimum

induced by the existence of the minimum wage may help explain why the average level of the P50-P10 is lower for women. Interestingly, the 1980s was a period during which the US federal minimum wage was held constant (from January 1981) in nominal terms, and declined dramatically in real terms.[19] Assuming inequality at the bottom of the female wage distribution is particularly sensitive to changes in the minimum wage, this helps explain the sharp increase in the female P50-P10 wage ratio over this decade.

The level of inequality at the top of the wage distribution as measured by the 90th-50th percentile ratio (P90-P50) is similar for men and women. Inequality at the top increases throughout the sample period, and especially after 1980, with wages at the 90th percentile rising slightly more for men than for women, relative to the corresponding median.

To summarize, the increases in US wage dispersion in (i) the 1970s, (ii) the 1980s, and (iii) the 1990s were concentrated, respectively, within (i) the bottom half of the wage distribution, (ii) through the wage distribution, and (iii) in the top half of the wage distribution.

There is a large empirical literature documenting the evolution of cross-sectional wage inequality in the United States since the mid 1960s. The two most recent and comprehensive surveys are Katz and Autor (1999), and Eckstein and Nagypal (2004). A more up to date account is provided by Autor, Katz and Kearney (2008).[20] All these papers are based on CPS data, and focus only on full-time, full-year workers, i.e. individuals who work at least 35 hours per week and forty-plus weeks per year. Our analysis is based on a much broader sample, given the more inclusive criterion for hours worked. Nevertheless, the qualitative trends we uncover are very similar to these previous studies. A unique contribution of our study (see Section 6) will be to document that measured changes in the wage structure in the CEX and the PSID line up very well with those in the larger CPS sample.

Observables and residuals In order to understand the sources of the rise in US wage inequality, it is important to distinguish the role of some key observable demographics such as education, age and gender. We perform this decomposition in Figure 5. We define the male

in 2002, compared to 2 percent of men. For more details on the characteristics of minimum wage workers see http://www.bls.gov/cps/minwage2002.htm

[19] Lee (1999) and Card and DiNardo (2002) claim that the US federal minimum wage has a large impact in shaping the bottom of the wage distribution. The real minimum wage was stable at around \$8.50 (in 2008 dollars) between 1967 and 1979, then declined steadily to reach \$5.50 in 1990. If plotted together, the inverse of the real minimum wage and the P50-P10 ratio comove very closely, especially for women.

[20] Historically, the widening of the US wage structure during the 1980s was first documented by Davis and Haltiwanger (1991), Bound and Johnson (1992), Katz and Murphy (1992), Levy and Murnane (1992), Murphy and Welch (1992), and Juhn, Murphy and Pierce (1993), among others.

education premium as the ratio between the average hourly wage of male workers with at least 16 years of schooling to the average wage of male workers with less than 16 years of schooling. The pattern that emerges is the well documented U-shape: following a decline until the late 1970s, the college wage premium starts rising steadily. In 1975, US college graduates earned 40% more than high-school graduates, while in 2005 they earned 90% more.

In the US, the fraction of men 25 and older who have completed college rose steadily from 13% in 1967 to 29% in 2005 (US Census Bureau). A vast literature argues that trends in relative quantities and prices for college-educated labor reflect a skill-biased demand shift, which economists have associated with the technological shift towards information and communications technology (ICT) and to globalization (e.g., Katz and Murphy, 1992; Krusell et al., 2000; Acemoglu, 2002; Hornstein et al., 2005).[21]

The experience (age) wage premium plotted in Figure 5 is defined as the ratio between the average hourly wage of 45-55 year-olds and the hourly wage of 25-35 year-olds. The male experience premium more than doubles (from 20% to 40%) between 1975 and the end of the sample period. The increase for women is smaller and occurs somewhat later. Qualitatively, these trends are consistent with the evolution of relative quantities. As the "baby-boom generation" started to enter the labor market in the early 1970s, the relative labor supply of the 25-35 year-olds started to rise, implying rising relative scarcity (and price) for older workers. By 1990, these boomers were transiting into the 45-55 age group, depressing the experience premium.[22]

The plot of the gender wage premium in Figure 5 shows that, on average, men earned 65% more per hour than women in 1975, but only 30% more in 2005. This convergence was concentrated in the 1980s: from the early 1990s there has been little additional reduction in the raw gender gap.

The last panel of Figure 5 displays residual wage inequality, measured as the variance of log wage residuals from a regression on standard demographics.[23] Residual wage dispersion rises throughout the period. A comparison with the variance of "raw" wage inequality (see the first panel of Figure 4) reveals that residual inequality explains essentially all of the increase in

[21] Eckstein and Nagypal (2004) and, more recently, Lemieux (2006) document that the premium for post-graduate education increased even faster.

[22] Eckstein and Nagypal (2002, Figure 15) plot the coefficient on experience from a standard Mincerian wage regression and find a pattern very similar to ours: the experience premium for women is much lower than for men, and for both sexes it rises in the 1970s and 1980s and stabilizes in the 1990s.

[23] See the Appendix for the exact regression specification.

cross-sectional male wage dispersion in the 1970s, but only about two thirds of the rise since 1980 – the rest being explained by observable characteristics, particularly experience in the 1980s and education in the 1980s and 1990s.

Labor supply The top-left panel of Figure 6 plots the variance of log earnings for men and women. The variance of male earnings increases by 30 log points over the sample period, with two third of this increase concentrated between 1967 and 1982. Dispersion in female earnings, in sharp contrast, is essentially trendless. It is perhaps surprising that the pictures for dispersion in earnings looks so different from those for dispersion in wages in Figure 4, given that we measure wages as earnings per hour.

Mechanically, the variance of log earnings is equal to the variance of log wages plus the variance of log hours plus twice the covariance between log wages and log hours. With this in mind, the top-right panel of Figure 6 indicates that the variance of log female hours falls from 0.28 to 0.20, which partially offsets the impact of rising wage dispersion on female earnings inequality. This decline in female hours dispersion towards the level for men mirrors the convergence in female wages and hours (recall Figure 2). While inequality in male hours is sharply counter-cyclical, it exhibits no obvious long run trend, averaging 0.12 over the sample period.

The bottom-left panel of Figure 6 shows the correlation between log wages and log hours, and sheds light on the dramatic increase in the variance of male earnings. In particular, the correlation increases sharply in the first half of the sample period, precisely where the increase in earnings dispersion is concentrated, before flattening off. The bottom-right panel indicates that this correlation rose both because low wage men reduced their hours, and because high wage men increased their hours.[24] Female wages and hours are more strongly positively correlated their male counterparts on average, but the rise in female correlation is less marked.

Earnings Figure 7 delves deeper into the evolution of inequality in male earnings. Here we rank men by earnings, and for each decile of the earnings distribution compute average hours and average wages. To focus on dynamics, we plot log changes for each variable relative to 1967.[25] The top-left panel of the figure indicates that, relative to 1967, earnings of the bottom decile declined in real terms by 60 percent in the period up to 1982 before recovering somewhat in the 1990s. Earnings for the top decile rose steadily throughout the sample period.

[24] To produce this figure we divided men in Sample C into ten bins corresponding to deciles in the wage distribution. We then computed the log deviation, relative to 1967, in average hours worked within each bin.

[25] In terms of levels, in every year both average wages and average hours increase monotonically across the bins ranked by earnings.

The top-right and bottom-left panels of the figure make a striking point: earnings dynamics at the bottom of the male earnings distribution are almost entirely driven by changes in hours, while earnings dynamics at the top of the distribution are almost entirely driven by changes in wages. To see this, note that wage dynamics for the bottom decile of the earnings distribution are very similar to those for the fourth decile, while hours for these two groups evolve very differently: hours for the fourth earnings decile are very stable, while hours for the bottom decile fluctuate dramatically as a virtual mirror image of the unemployment rate (the bottom-right panel). Conversely, the dynamics for hours at the top of the male earnings distribution are stable and very similar to those for the fourth decile, while wages consistently grow more rapidly.

To recap, the key to understanding the evolution of the top of the male earnings distribution is to understand the evolution of the top of the male wage distribution, while the key to understanding the evolution of the bottom of the earnings distribution is to understand the evolution of hours worked and the unemployment rate.

Interpretation Put in a broader macro context, trends in earnings inequality appear to be shaped by two forces: aggregate labor demand shifts, and institutional constraints (unions, minimum wage) operating in the labor market. At the top of the distribution –where it is wages that drive earnings dynamics– institutional constraints are largely absent, and hence labor demand shifts in favor of skilled workers increase both wage and earnings inequality. Consistently with this interpretation, we note that the pattern for the college-high school premium (Figure 5) is similar to that for the P90-P50 wage ratio (Figure 4), suggesting that increasing demand for educated labor is a major factor widening inequality at the top.

For lower-skilled workers, unions and minimum wage laws deflect some of the impact of declining labor demand from prices (wages) to quantities (hours). In the 1970s, when these institutions were particularly strong, declining aggregate demand (the "TFP slowdown") and declining relative demand for unskilled labor (skill-biased technical change) translated into lower employment for low-skilled men (Figure 7) in addition to lower relative wages (Figure 4).[26] The combined effect was rapid growth in earnings inequality at the bottom. In the 1980s, institutional constraints lost some of their strength as unions weakened with the decline

[26]Here we present the productivity slowdown and skill-biased demand shifts as two separate phenomena. However, economists have advanced a common interpretation for both based on learning effects associated to the introduction of ICT. See Hornstein et al. (2005), and the references therein.

of the manufacturing sector, while the real value of the federal minimum wage was eroded by inflation. Thus in this period, the impact of labor demand shocks at the bottom of the distribution shifted from quantities to prices: wages fell sharply, but hours worked partially recovered. The combined effect was slower growth in earnings inequality. In the 1990s, the real minimum wage stabilized, while aggregate productivity growth recovered. The net effect was broad stability at the bottom of the wage and earnings distributions.

4.2 Household-level inequality

Equivalized household earnings Figure 8 plots four measures of dispersion in household earnings, where each household's income is first adjusted to a per-adult-equivalent basis using the OECD equivalence scale.[27] The top-left and bottom-left panels plot, respectively, the variance of log earnings and the P50-P10 ratio. These two series track each other closely. Qualitatively, this is not surprising, since the logarithmic function effectively amplifies small earnings values, but the quantitative impact is strikingly large. The variance of household earnings rises rapidly in the 1970s and early 1980s before stabilizing. Qualitatively the profile is similar to that for male earnings in Figure 6.[28]

The top-right and bottom-right panels plot the Gini coefficient for household earnings and the P90-P50 ratio. These two series are also qualitatively very similar, reflecting the sensitivity of the Gini coefficient to the shape of the upper portion of the earnings distribution. Inequality at the top of the household earnings distribution increases steadily across the entire sample period. However, comparing the evolution of the P90-P50 and P50-P10 ratios, it is clear that while the growth in the former is more continuous, it is much smaller in overall magnitude.

Residual inequality in household earnings The top-left panel of Figure 9 plots three versions of the variance of log household earnings in the CPS: non-equivalized, equivalized, and residual, where the residuals are computed from the same regression used in Figure 5. Equivalization reduces slightly the level, but has no impact on the trend of the variance, which increases by roughly 30 log points until the early 1990s, and then levels off.

[27] The relevant sample for the statistics on household-level inequality is all households in Sample B with positive household earnings. In addition we trim we trim the bottom 0.5% of the distribution because the variance of logs is very sensitive to low outliers.

[28] The difference between the two series primarily reflects the fact that in Figure 6 we plot the variance of male earnings for men working at least 260 hours, while in Figure 8 there is no explicit selection on hours. Without this hours restriction, the variance of male earnings is essentially flat after the mid 1980s, just like the variance of equivalized household earnings.

The figure shows that key household demographic characteristics explain about 40% of the variance of household earnings. Consistently with what we observed for wages, growth in residual earnings dispersion accounts for most of the increase in the raw variance.

Cyclical dynamics of earnings inequality Figure 10 plots the trends in percentiles at different points in the distribution for household earnings (all normalized to zero in 1967), together with shaded areas denoting NBER-dated recessions. The panel shows clearly the fanning out of the distribution over time. While the top 5th of the distribution have seen household earnings rise in real terms by around 60 log points over the sample period, those below the 10th percentile earned no more in 2005 than in 1970. Earnings inequality tends to widen sharply in recessions, and then remains relatively stable during periods of expansion. This reflects the fact that while household earnings are procyclical at each percentile, business cycle fluctuations are much more severe at the bottom of the distribution, with large percentage declines in earnings during recessions. Indeed, the 5th and 10th earnings percentiles closely mirror - inversely - the time path for the unemployment rate over the sample period.[29]

Broader measures of income Figure 11 displays the evolution of various measures of cross-sectional household income dispersion, beginning with labor earnings for the main earner, and moving to increasingly broad measures of household income.[30] To illustrate how inequality has changed over times at both ends of the income distribution, we plot both the variance of log and the Gini coefficient.

Moving from earnings for the main earner to total household earnings increases slightly the average level of the variance of log income, but reduces the Gini coefficient for income. The first finding indicates that households with very low main earner earnings typically receive no labor income from other household members, in part because many low-earning households contain only one working-age adult. The second finding indicates that at the top of the household earnings distribution, where most households are married couples, spousal earnings are imperfectly correlated with earnings of the main earner.

One might have expected that, to the extent that the family is a source of insurance against individual risk, inequality in household earnings would have increased by less over time than

[29]The troughs of the low-end percentiles in 1971, 1975, 1982, 1993 and 2004 corresponding almost exactly to turning points in the unemployment rate in 1971, 1975, 1982, 1992 and 2003.

[30]For each type of income, moments are computed for the same set of households: households in Sample B that also have positive household earnings. We trim the bottom 0.5 percent of observations according to the particular definition of income plotted.

inequality in individual earnings. Moreover, the rise in female participation documented in Section 3 ought to have further mitigated the rise in household earnings inequality. When inequality is measured by the Gini coefficient, increasing within-family insurance is indeed apparent: the Ginis for main-earner and household earnings rise by 10 and 8 points respectively over the sample period. However, at the bottom of the household earnings distribution, the scope for greater within-family risk sharing for married couple households is offset at the aggregate level by an upward trend in the fraction of single-adult households, such that the variance of log household earnings and log main-earner earnings increase by the same amount.[31]

In moving beyond earnings to broader measures of income, it is important to keep two things in mind. First, our focus is on households containing at least one adult of working age. Thus we miss most older households, which rely primarily on unearned income. Second, recall that most categories of unearned income suffer from serious under-reporting in the March CPS and in other household surveys (see Section 3).

With these important caveats in mind, we note that adding private transfers reduces income inequality mostly at the bottom. In part, this reflects the fact that households containing retirees tend to have lower earnings, but higher private retirement income. Adding asset income has little impact on the variance of log income, except for increasing inequality slightly towards the end of the sample period. In contrast, including asset income increases markedly the Gini coefficient for income. This reflects the well-known fact that a large fraction of aggregate wealth is concentrated at the top of the wealth distribution, and that wealth and income are positively correlated in cross-section.[32]

Public transfers play a very important role in compressing inequality at the bottom of the distribution, as evident from the much wider gap between pre-government and pre-tax income in the variance of log than in the Gini coefficient. Up until 1982, public transfers serve as a powerful force mitigating rising inequality in pre-government income. Thereafter, however, the income compression associated with public transfers declines. These dynamics reflect the fact that the extent of insurance provided through public transfers co-varies strongly with the unemployment rate: public insurance rose in the 1970s as the unemployment rate ratcheted upwards, and declined after the 1980-82 recession, as the unemployment rate trended down.[33]

[31] Fitzgerald (2008) provides an analysis of income dynamics for all sorts of household-types, and also describes how the mix of different types has changed over time.

[32] For example, Budria et al. (1998) report a Gini for wealth of 0.8 in the 1998 Survey of Consumer Finances, and a correlation between wealth and income of 0.6.

[33] An additional reduction in the redistributive role of public transfers follows the PRWORA Act of 1996,

The tax code also appears to be quite progressive overall, reducing the variance of pre-tax income by around 10 log points. In the 1980s, pre-tax and post-tax income follow very similar trends. In the 1990s, by contrast, the gap between pre- and post-tax income inequality rises. These trends are consistent with the view that the taxes became less progressive under Reagan (1981-1989), and more progressive under Clinton (1993-2001): Piketty and Saez (2006) report that federal tax rates declined sharply at the top of the income distribution in the 1980s, and then increased somewhat in the 1990s (see their Table 2).

Consumption inequality Figure 12 documents the evolution of inequality in equivalized non-durable consumption expenditures (as reported in the CEX) across households in the United States. For each measure of dispersion, we also report inequality in CEX-based measures of equivalized household earnings and equivalized household disposable income. All inequality measures are computed on the same sample of households, which is sample B described above. Using the same sample of households for all measures excludes sample variation as a source of discrepancy between income and consumption inequality but, as we discuss later in Section 6, trends in the measures of dispersion for earnings and disposable income in the CEX line up fairly closely with the corresponding series in the CPS and the PSID.[34]

The top-left plot shows the variance of logs. The variance of log earnings increases sharply in the early 1980s, and is then essentially constant. The increase over the sample period is around 12 log points. The variance of disposable income is lower than the variance of earnings and has a somewhat different trend: after a spike in the early 1980s, it continues to rise, and rises cumulatively by 18 log points between 1980 and 2006. Figure 11 above suggests that the gap between dispersion in earnings and dispersion in disposable income is primarily due taxes and transfers. In this light, the fact that the gap appears to be narrowing indicates that the overall "equalizing" effect of taxes and transfers on household income weakened between 1980 and 2006. This also applies to top of the distribution, as the Gini coefficients for earnings and disposable income also converge over time (top-right panel). Inequality at the top, as measured by Gini coefficients or P90-P50 ratios, increases steadily through the sample period, consistently with our previous finding from the CPS.

Regarding inequality in consumption, Figure 12 shows three interesting facts. First, rising

which reformed Federal cash assistance to the poor (see Moffitt, 2008).

[34] One exception is the variance of log disposable income, which displays a larger increase (20 log points) in the CEX than in the CPS or the PSID (around 10 log points). See Section 6 for more on this.

inequality in disposable income up to 2000 seems to have had very little effect on consumption inequality (for more on this see, for example, Krueger and Perri, 2006). The second fact, which has not been noted before, is that after 2001 the consumption Gini increases quite substantially, even though the P90-P50 ratio is relatively flat. This suggests that rising inequality in consumption at the very top of the distribution. Indeed we find that the share of consumption expenditures of the top five percent of the consumption distribution increased from a fairly constant level of 15% throughout the 1990s to 16% in the period 2003-2006. Third, the gap between the P50-P10 ratios for disposable income and consumption is much larger than the gap between the corresponding P90-P50 ratios. One possible explanation for this finding is that income differences between the median household and an household at the bottom of the distribution are more likely to be of a temporary nature (e.g., unemployment) and thus do not translate into consumption, while differences between the median household and an household at the top of the distribution are of a more permanent nature (e.g., skills), and thus show up in consumption inequality.

4.3 Taking stock

To give an overview of the evolution of inequality over our sample period, it is useful to divide it into three sub-periods: (i) the late 1960s and 1970s, (ii) the 1980s, and (iii) the 1990s and early 2000s.

In the first period, the gap between male wages at the bottom of the wage distribution and the median grew, while the top of the wage distribution was relatively stable. The decline in wages for low-wage men was compounded by the fact that these workers bore the brunt of the increase in unemployment over this period: the unemployment rate rose from less than four percent to almost ten percent between 1967 and 1982. Thus the variance of log male earnings increased dramatically over this period. The variance of household income increased much less than the variance of household earnings, because social insurance programs partially replaced declining earnings for low-income households.

In the 1980s, inequality rose rapidly throughout the male wage distribution. At the top, this translated directly into widening earnings inequality. However, after the 1980-82 recession, hours at the bottom of the male earnings distribution rose even as wages fell. Thus earnings inequality at the bottom increased only modestly. Inequality at the bottom of the distribution of disposable household income increased somewhat more, reflecting a decline in public income support as the unemployment rate fell.

The 1990s looked much like the 1980s, except that inequality stabilized at the bottom of the wage and earnings distributions.

Over the post 1980 period for which CEX consumption data are available, we replicate previous findings that consumption dispersion has increased by less than dispersion in disposable household income (Slesnick, 2001; Krueger and Perri, 2006; Attanasio, Battistin, Ichimura, 2007). This suggests that some part of income inequality is effectively insurable in nature.

We follow a two-pronged approach to further investigate this issue. First, we look at the evolution of earnings, income and consumption inequality over the life-cycle. As emphasized by Deaton and Paxson (1994), the gap between the age-profile for consumption dispersion and the age profile for income dispersion is a metric for imperfect insurance. Second, we use the PSID to estimate dynamic models for wage risk with permanent and transitory components. The idea is that transitory shocks are largely insurable, while permanent shocks are largely uninsurable and thus ought to show up in consumption.

5 Inequality over the life-cycle

The age profiles for inequality in wages, hours, earnings and consumption contain lots of information about the nature of preferences, risk and insurance when organized within life-cycle models with heterogeneous agents and incomplete markets (see Deaton and Paxson, 1994; Storesletten, Telmer and Yaron, 2004a; Guvenen, 2007; Huggett, Ventura and Yaron, 2008; Kaplan, 2008; Kaplan and Violante, 2008).

However, isolating a pure age profile from repeated cross-sections in a non-stationary environment is challenging because age, time and cohort are linearly dependent (cohort is time minus age). Here, we follow Heathcote, Storesletten and Violante (2005) and report two sets of estimates for the evolution of dispersion by age. The first set controls for time effects, the second set for cohort effects.

More specifically, let $m_{a,c,t}$ be a cross-sectional moment of interest (e.g., the variance of log earnings) for the group of households, with head of age a belonging to cohort c (hence, observed at date $t = c + a$). To isolate the age profile, we run the two alternative regressions

$$\begin{aligned} m_{a,c,t} &= \boldsymbol{\beta}_a'\mathbf{D}_a + \boldsymbol{\beta}_t'\mathbf{D}_t + \varepsilon_{a,c,t} \qquad (1) \\ m_{a,c,t} &= \boldsymbol{\beta}_a'\mathbf{D}_a + \boldsymbol{\beta}_c'\mathbf{D}_c + \varepsilon_{a,c,t}, \end{aligned}$$

where $\mathbf{D}_t, \mathbf{D}_c$ and $\mathbf{D}_a$ are vectors with entries corresponding to a full set of year, cohort and age dummies, respectively. The vectors $\boldsymbol{\beta}_t$, $\boldsymbol{\beta}_c$ and $\boldsymbol{\beta}_a$ are the corresponding vectors of coefficients. The lines labelled "year effects" in Figure 13 plot the estimated values for $\boldsymbol{\beta}_a$ in the first regression where we control for year effects, and the lines labelled "cohort effects" plot the estimated values for $\boldsymbol{\beta}_a$ in the second regression, where we control for cohort effects only.

Another important issue in documenting the evolution of household inequality over the life-cycle is that the distribution over household size is time-varying. We therefore report both inequality in raw household-level variables, without adjusting for size, and in equivalized household income, where we use the OECD equivalence scale to express earnings, income and consumption in per-adult-equivalent units.[35]

To allow for a straightforward comparison of how inequality in earnings, income and consumption evolve with age, all the series plotted in Figure 13 are based on the same sample: sample B from the CEX. Because the CEX sample is relatively small, rather than estimating a full set of age dummies, we group observations in 5-year age groups. The series are normalized so that each starts at zero at age 27, which is the midpoint of the first 5-year age group (25-29).

The figure shows that the variance of log household earnings rises over the life-cycle by more than the variance of disposable income, which in turn rises by more than the variance of log consumption. The fact that dispersion in consumption grows less rapidly than dispersion in income indicates that households are able to effectively insure some fraction of persistent income fluctuations.

Cohort vs. time The precise magnitudes of the life-cycle increases in inequality are sensitive to whether one controls for year or cohort effects. For example, the variance of log disposable income rises twice as fast under the cohort view (the right-hand-side panels) than under the time view (the left-hand-side panels). Why is the life-cycle profile for income so sensitive to whether one adopts the time or cohort view, while the earnings and consumption profiles look more similar? Recall from Figure 12 that the cross-sectional variances of log earnings and log consumption are relatively stable over time in the CEX, while the variance

[35] An alternative way to equivalize is to regress household earnings (or income or consumption) on household characteristics (e.g., number of adults, number of children) and to use the predicted values for earnings for each household type as the scaling factors. Regression-based equivalence scales differ dramatically from the OECD scale we use. For example, the OECD treats additional children as enlarging the effective household size (reducing per-equivalent earnings), while according to the regression, additional children predict lower earnings, and thus reduce effective family size. The OECD approach likely better captures true economies of scale within the household.

of disposable income shows a marked increase. Thus, whether non-stationarity is modelled through year or cohort effects should have relatively little impact on the implied age profiles for earnings or consumption inequality, whereas more is at stake in deciding whether to model rising income inequality through time or cohort effects. If one takes the pure cohort view, cross-sectional inequality can only increase if each successive cohort starts out with more unequal income. If one takes the pure time view, cross-sectional inequality can only increase if all cohorts see faster growth in within-cohort inequality. The right-hand-side panels of Figure 13 indicate that over this period, within-cohort income inequality was rising rapidly, while the left-hand-side panels indicate that the time-effect model attributes much of this growth to a general increase in income inequality over time. Heathcote et al. (2005) argued formally that time effects have played an important role in the evolution of US inequality, while there is little evidence in favor of cohort effects.

Equivalizing The size of the life-cycle growth in dispersion is sensitive to whether or not one focuses on raw or equivalized measures. Equivalizing reduces the estimated life-cycle increases for inequality for all variables. For example, under the cohort view the variance of log raw household consumption rises twice as fast as log equivalized consumption. Equivalizing reduces the overall growth in life-cycle inequality primarily by compressing growth in inequality in the middle of the life-cycle. In part this is because equivalizing has the effect of amplifying income inequality for the youngest households in our sample, but has less impact on measured inequality for older households. This is consistent with the tendency of lower-income individuals to marry and have children at younger ages.

Curvature of the profiles Finally, the profiles for income and consumption inequality over the life-cycle exhibit differential curvature. The consumption profile is concave: inequality rises until roughly age 50, and is approximately flat thereafter. The earnings profile is convex, reflecting an acceleration in earnings inequality at older ages. The concavity in consumption reflects the fact that as retirement approaches, the within-cohort distribution of permanent income stabilizes (see, for example, Storesletten et al. 2004a). Convexity of the earnings profile has been indicated as evidence of "heterogeneous income profiles" (Lillard and Weiss, 1979; Baker, 1997; Guvenen, 2007), since an income process featuring only a unit root, or a persistent autoregressive component, would induce a linear or concave earnings profile.[36]

[36]See Guvenen (2007) for a formal explanation of why the model with heterogeneous income profiles can generate a convexity in the variance of earnings over the life cycle.

However, it is important to remember that the life-cycle profile for dispersion in earnings inherits the corresponding profiles for dispersion in wages and hours. Figure 14, discussed in the next section, indicates that the life-cycle profile for the variance of log wages is slightly concave, and that the convexity of the earnings profile reflects increasing dispersion in hours worked at older ages, as individuals begin the transition to retirement. The fact that convexity in the life-cycle profile for earnings is attributable to (arguably endogenous) hours rather than to (arguably exogenous) wages weakens the case for profile heterogeneity.

6 Comparison across datasets

Life-cycle Figures 14 compares the evolution of inequality over the life-cycle across our CPS, PSID and CEX samples. For all variables – head wage, head hours, raw household earnings, and OECD-equivalized household earnings– we find very close alignment across the three datasets. As discussed above, the life-cycle profile for the variance of log wages is concave, but the dramatic U-shape in the variance of log hours translates into a convex profile for the variance of log household earnings. Figure 14 plots age profiles controlling for year effects (see Section 5).[37] We also computed the same series under the cohort view, and once again found a remarkable degree of cohesion across datasets.

Time-series of averages With respect to per-capita averages, we have verified that both the levels and the trends of per-capita income in the CPS and PSID are very similar. CEX per capita income is roughly 15 percent lower on average, but it grows at a similar rate, except for the post-2000 period, when it grows somewhat faster.

Time-series of inequality Figures 15 and 16 compare the evolution of inequality in male wages and hours, and in equivalized household earnings and disposable income across our three datasets. Figure 15 shows inequality measured as variance of log, while Figure 16 plots Gini coefficients.

The top two panels of these two figures indicate broad agreement across datasets regarding inequality in wages and hours, at both ends of their respective distributions. The profiles for male wages in the CPS and the PSID align especially closely. The overall trends for male wages in the CEX are similar, but the CEX series is more volatile and indicates a more rapid

[37] For the large CPS sample we estimated a full set of age dummies, rather than grouping observations in 5-year age groups.

increase in both the variance of log wages and the Gini coefficient for wages in the early 1980s. Compared to the CPS, the variance of log male hours is slightly lower in the PSID, and slightly higher in the CEX, though the cyclical fluctuations are remarkably similar in all three series.

A debate has developed recently on whether the rise in US inequality was mostly an episodic event of the 1980s which plateaued by the end of the decade and never recurred (Card and DiNardo, 2002; Lemieux, 2006) or, rather, a long-term trend towards more wage inequality (Autor, Katz, and Kearney, 2008) that started in the 1970s and is ongoing. The "episodic" interpretation of widening wage dispersion is based on the May Outgoing Rotation Group (ORG) samples of the CPS which has point-in-time measures of usual hourly wages. The "long-run" interpretation is based on the March CPS, the data we use, where hourly wages are constructed as annual earnings divided by annual hours worked. Interestingly, we find that both the PSID and the CEX give support to the "long-run" view.[38] Moreover, after 2000 one observes renewed growth in inequality at the bottom of the wage distribution in all three data sets.

The bottom-left panels of Figures 15 and 16 plot our two measures of dispersion for equivalized household earnings. The Gini coefficients for household earnings in the three datasets track each other very closely through the entire sample period. The variance of log earnings in the CPS and CEX also line up closely over the 1980-2005 period where both are available. However, the same panel shows a noticeable difference in the 1970s between the CPS and the PSID: the variance of household earnings in the CPS rises rapidly, while the corresponding series for the PSID is quite flat.

The series for dispersion in disposable income plotted in the bottom-right panels of Figures 15 and 16 show some differences in terms of levels, but broad agreement with respect to trends over time, especially when dispersion is measured by the Gini coefficient. The CPS and PSID series for the variance of log disposable income exhibit similar trends, while the corresponding CEX series increases more rapidly.

The fact that the discrepancy between the CEX and the other data sets appears in disposable income but not in earnings means that it is due to differential dynamics for unearned income or taxes. To explore more the issue we computed a time series for the variance of pre-tax income in the CEX, and found that it tracks the corresponding series in the CPS. This suggests that taxes

[38] It should be noted, however, that our measure of hourly wages in the PSID and the CEX is constructed as annual earnings divided by hours worked last year, as in the March CPS.

are the main reason for why the two datasets diverge with respect to the variance of disposable income. It remains an open question whether CPS imputed taxes or CEX self-reported taxes are a more accurate measure of households' actual tax burdens.

We conclude that comparing these datasets is a very useful exercise for students of inequality. The close alignment we find across the CPS and the CEX with respect to wages and earnings should give researchers more confidence when integrating CPS wage/earnings data and CEX consumption data. The close alignment we find with respect to wages across the CPS and the PSID should give researchers more confidence that models for wage dynamics estimated from the PSID panel data are consistent with the evolution of cross-sectional wage dispersion in the much larger CPS sample.

Variance of earnings: CPS versus PSID The only striking discrepancy across datasets that we detect is the sharp increase in the variance of CPS household earnings in the 1970s which is not apparent in the PSID. At a mechanical level, the difference can be attributed to the fact that over the period 1967-1982, the PSID reveals a much smaller drop in male and household earnings at the very bottom of their respective distributions (above the second decile of the distribution, household earnings in the CPS and PSID track each other closely). Male earnings decline by less because male hours decline by less: the change in wages at the bottom of the distributions is similar across the two datasets.

To understand why the bottom of the PSID earnings distribution evolves differently than the other datasets, it is useful to review some important differences in survey design. The CPS and CEX are designed to be representative of the US population in each year. The PSID was designed to be representative of the US population in 1967, and in subsequent years has tracked the original families and their descendants. There are two reasons why the PSID is likely to be imperfectly representative in later years. First, the basic SRC sample under-represents recent immigrants, since by definition immigrants cannot be descendants of the original sample. Second, over the years there has been significant cumulative attrition from the original sample: over 50 percent by 1988. The PSID provides weights designed to adjust for the effects of attrition, but they do not provide weights for the SRC sample, which is the sample we use. Fitzgerald et al. (1998) report that attritors are disproportionately non-white, older, and less educated. They are less likely to be married, and more likely to rent and to receive welfare. Attritors also work less and earn less, and have more volatile income.

Fitzgerald et al. compare a large set of demographic and income moments across the CPS and PSID in 1967 and 1988. They find that, with respect to first moments, the PSID remained fairly representative over this period, in part because some of the events that lead individuals to drop out of the sample (like unemployment) tend to be relatively transitory, so that selective attrition does not lead to permanent unrepresentativeness. Still, even if PSID first moments are broadly representative, it seems likely that the PSID is less representative of the bottom of the earnings and income distributions, and that this problem may have grown over time as the shares of non-white and non-married individuals in the CPS and CEX have grown more rapidly that in the PSID (see Table 2). Another reason to suspect that the PSID understates the declines in individual earnings in the lowest percentiles of the earnings distribution in the 1967-1982 period is that a decline in earnings (e.g., unemployment) increases the probability of attritting: thus attrition is particularly problematic during a period of rising unemployment and labor market instability.[39]

There is one more interesting wrinkle to add to the CPS-PSID comparison. Figure 15 compares inequality in equivalized household earnings. Figure 9 shows that the CPS profiles for raw and equivalized household earnings are very similar. In the PSID, however, the time path for raw household earnings inequality (not shown) is quite a bit steeper than that for equivalized earnings. The finding that equivalizing impacts inequality differentially across the datasets is related to the discrepancy in the number of households with spouse present documented in Table 2. In particular, the variance in the number of adults per household increases over the 1967-1982 period in the CPS, while this variance declines over the same period in the PSID. This is consistent with the Fitzgerald et al. finding of a positive association between marital dissolution and attrition in the PSID.

7 Income dynamics

In labor economics, there is a long tradition of estimating structural models of income dynamics from panel data (starting from Lillard and Willis, 1978; Lillard and Weiss, 1979; MaCurdy, 1982). These models have recently been adopted by quantitative macroeconomists as a key ingredient in the calibration and estimation of heterogeneous-agent incomplete-markets models (e.g., Imrohoroglu, 1989; Huggett, 1993; Aiyagari, 1994; Rios-Rull, 1996).

[39]Because the PSID under-represents those with low or zero earnings, it under-estimates poverty. The empirical literature on poverty consistently finds that poverty rates are lower in the PSID than in the March CPS (see, for example, Duncan and Rodgers, 1991, Figure 1).

In this section, we use the panel dimension of PSID data (Sample C) to estimate the dynamics of individual wages in the United States for the period 1968-1996.[40] We choose to focus on log hourly wage dynamics since wages are the most primitive (i.e., closest to being exogenous) among the various income measures we analyze. We restrict attention to heads of households, since endogenous selection into work undermines the estimation of wage dynamics for the secondary earner.

As is common in the literature, we focus on "residual" dispersion, i.e., log wage residuals from a standard Mincerian regression with the same specification chosen for Figure 5. The variance of residual wage inequality grew by about 12 log points over the 1968-1996 period in both the CPS and the PSID. As a result of this upward trend, the statistical model is estimated nonparametrically to allow for non-stationarity, a standard approach in this literature since Gottschalk and Moffitt (1994).

Statistical model Let $y_{i,a,t}$ be the residual log hourly wage for individual i of age a at date t. We estimate a permanent-transitory (PT) model of the form:

$$\begin{aligned} y_{i,a,t} &= z_{i,a,t} + \varepsilon_{i,a,t} \\ z_{i,a,t} &= z_{i,a-1,t-1} + \eta_{i,a,t} \end{aligned} \tag{2}$$

where $\varepsilon_{i,a,t}$ and $\eta_{i,a,t}$ are innovations which are uncorrelated over time, i.i.d. across individuals, and orthogonal to each other. Let $\sigma_{\varepsilon t}$ and $\sigma_{\eta t}$ denote $var_t\left(\varepsilon_{i,a,t}\right)$ and $var_t\left(\eta_{i,a,t}\right)$ respectively. As the notation suggests, these conditional variances are time-varying, but do not depend on age. For new entrants of age $a = 0$ (corresponding to actual age 25) the initial variance of the permanent component $z_{i,0,t}$ is drawn from a distribution with cohort-specific variance $\sigma_{z0,t}$. Thus our model for wage dynamics effectively incorporates cohort effects.

Methodology The literature has followed two alternative approaches in estimating income processes. The first, common in labor economics (e.g., Abowd and Card, 1989; Meghir and Pistaferri, 2004; Blundell, Pistaferri and Preston, 2008), uses moments based on income growth rates – or first-differences in log income. The second, more common in macroeconomic applications (e.g., Storesletten et al. 2004b; Guvenen, 2007; Heathcote et al. 2008) uses moments in log income levels. Although either approach can be used to estimate the permanent-

[40] We discard the data for 1967 since the attrition between 1967 and 1968 is especially high (see Fitzgerald et al. 1997). Since 1996 the PSID survey has been administered bi-annually, and some model parameters are not identified in the missing years.

transitory model described above, they differ with respect to the set of moments that identify the structural parameters $\{\sigma_{\varepsilon t}, \sigma_{\eta t}, \sigma_{z0,t}\}$.

In growth rates, the model is usually estimated based on the following restrictions:

$$cov_t\left(\Delta y_{i,a,t}, \Delta y_{i,a-j,t-j}\right) = \begin{cases} \sigma_{\eta t} + \sigma_{\varepsilon t} + \sigma_{\varepsilon,t-1} & j = 0 \\ -\sigma_{\varepsilon,t-1} & j = 1 \\ 0 & j > 1 \end{cases} \tag{3}$$

Thus, the covariance between growth rates at one lag ($j = 1$) identifies the variance of the transitory shock, while the variance of growth rates identifies, residually, the variance of permanent shocks. With an estimate for $\sigma_{\varepsilon t}$ in hand, the cohort-specific residual variance for labor market entrants identifies the cohort-specific variance $\sigma_{z0,t}$ through the relationship $var_t\left(y_{i,0,t}\right) = \sigma_{z0,t} + \sigma_{\varepsilon t}$. When covariances are computed for the whole cross-section (the approach we follow), the model is just identified.[41]

In levels, the same model is estimated based on moment restrictions of the type:

$$cov_{a,t}\left(y_{i,a,t}, y_{i,a-j,t-j}\right) = \begin{cases} var\left(z_{i,a,t}\right) + \sigma_{\varepsilon t} & j = 0 \\ var\left(z_{i,a-j,t-j}\right) & j > 0, \text{ and } t, a > j \end{cases} \tag{4}$$

where

$$var_{a,t}\left(z_{i,a,t}\right) = \begin{cases} \sigma_{z0,t} & a = 0 \\ \sigma_{z0,t-a} + \sum_{j=0}^{a-1} \sigma_{\eta,t-j} & a > 0. \end{cases} \tag{5}$$

In the estimation in levels we partition individuals into age groups in order to increase the number of observations used to calculate each covariance. In particular, "age" a in the model corresponds to ages $a-1, a, a+1$ in the data. The statistical model is overidentified: we use over 12,000 moments for this estimation.

We estimate the model following both approaches and compare findings. Throughout the analysis, we use a minimum distance estimator (Chamberlain, 1984), with moments weighted by the identity matrix as suggested by the Monte Carlo study of Altonji and Segal (1996), the standard methodology in the literature. It should be noted that, if the model is not mis-specified, both set of moments should deliver similar parameter estimates.[42]

Findings The parameter estimates for the simple permanent-transitory model for wages are plotted in Figure 17. It is immediately obvious that the choice of whether to target moments in growth rates or in levels when estimating the model leads to dramatically different sets

[41] Alternatively, one could compute cohort-specific covariances, and the model would be overidentified. In either case, it is easy to see that $\sigma_{\eta,1968}$ is not identified, since 1968 is the first year in the sample.

[42] The hypothesis that small sample bias could be stronger with one set of moments than with another is ruled out by Domeij and Floden (this issue) who run a series of Monte Carlo experiments.

of parameter estimates. We begin by discussing the estimates based on growth rates. The transitory variance rises in the early 1970s, and then it is remarkably stable until 1992 when it displays a discrete upward jump. Unfortunately the jump coincides with the switch in PSID data collection methods from telephone-based to computer-aided, which suggests that it may not reflect a genuine rise in productivity dispersion. The conditional variance of the permanent component rises from 0.03 to over 0.04 with the growth concentrated in the decade 1975-1985. The initial variance at age 25 starts at around 0.15 for the cohorts entering in the early 1970s and then rises to 0.18 around 1980.

We now turn to the estimates based on moments in levels. The transitory variance is almost three times as large as the growth-rate-based estimate, and it displays a steadier upward trend throughout the sample period. Conversely, the conditional variance of the permanent component is almost three times as small. The conditional variance of permanent shocks is hump-shaped, rising in the decade 1975-1985 before declining again. Finally, the initial residual wage variance at age 25 is generally increasing over time, and appears to be pro-cyclical, with peaks in 1975, 1982, and 1990.

According to the model estimated in levels, roughly 40% of the total increase of inequality over the period 1968-1996 can be accounted for by the permanent component, and 60% by the transitory component.[43] The rise in permanent inequality is concentrated in the 1980s (bottom-right panel), a period when the variance of log consumption was also rising (see Figure 12).

The model estimated in growth rates predicts an enormous, and we will argue, non-credible increase in the permanent component over time, reflecting the very large estimates for the conditional variances in the top-right panel.

Fit The divergence in the estimates obtained through the two approaches is striking. Which methodology provides a better fit? To answer this question we have isolated four key empirical moments from the data: (i) the age profile for the variance of log wages, (ii) the autocorrelation function of log wages, (iii) the variance of wage growth rates, and (iv) the covariance of wage growth rates at one lag. Figure 18 plots the fit of the model under the two sets of estimates.

Because it is exactly identified, the estimation based on growth rates fits perfectly the last

[43]The unconditional permanent variance in the bottom-right panel of Figure 17 changes over time as (i) old cohorts exit reducing the current permanent variance, (ii) dispersion within surviving cohorts increases according to the conditional variance of permanent innovations (top-right panel), and (iii) entering cohorts draw from the initial distribution with cohort-specific variance (bottom-left panel).

two moments. However, it predicts a rise in wage inequality over the life-cycle which is grossly counter-factual – more than twice as large as in the data. This is the result of the large estimate for $\sigma_{\eta t}$. To emphasize why these estimates for $\sigma_{\eta t}$ cannot be taken seriously, assume a working life of 35 years, and set $\sigma_{z0,t} = 0$, so that there is no permanent inequality between labor market entrants. Given the average estimated value for $\sigma_{\eta t}$ of 0.036, the average cross-sectional permanent variance would then be 0.63. But this is more than twice the average cross-sectional variance for residual wages, permanent and transitory components combined![44]

The fit of the autocorrelation function for the model based on growth rates is also very poor. The low estimated transitory variance is reflected in the small initial drop, the large conditional permanent variance in the systematic overestimation, and the upward trend in $\sigma_{\eta t}$ and $\sigma_{z0,t}$ in the steep downward trend.[45]

In contrast, the level-moment-based estimation fits perfectly the rise in wage dispersion over the life cycle, and it provides a much better fit to the autocovariance function. The fit for both moments in first-differences is poor in terms of levels, but rather good in terms of trends. Mechanically, the reason why the estimates in levels overpredict both first-difference moments in absolute value is that the estimated variance for transitory shocks is too large.

Given the substantial differences in parameter estimates when using the two set of moments, and given the fact that both sets of estimates have serious shortcomings in fitting overidentifying restrictions, we conclude that the permanent-transitory model is mis-specified. Thus future work should explore alternative models with the goal of finding a parsimonious specification that can broadly replicate all the moments plotted in Figure 18. Staying faithful to the simple permanent-transitory model in the meantime, we are inclined to cautiously embrace the parameter values obtained through moments in levels, and to discount the parameter estimates based on moments in growth rates, for the simple reason that only the former are consistent with overall cross-sectional dispersion, a first-order reality check.

To summarize, the main conclusions we draw from the time-series analysis of individual

[44] Some authors who have estimated PT models in the past (e.g., Blundell, Pistaferri and Preston, 2008) have trimmed log-differences to prevent the estimation to be affected by outliers and measurement error. When we repeated the estimation in first differences by excluding log-wage differences larger than one in absolute value, the average estimated value for $\sigma_{\eta t}$ falls from 0.036 to 0.025. However, the model still generates excessive cross-sectional dispersion.

[45] In a stationary world, the autocorrelation function of the PT model is L shaped. However, if the permanent variance and/or the initial permanent variance grow over time, time-aggregation can lead to a downward trend in the autocorrelation function because the most recent observations (those with the largest permanent component) only contribute to the shorter lags.

wage dynamics are two. First, the permanent-transitory decomposition of wage dispersion over the period 1968-1996 is coherent with the pattern of consumption inequality documented in Section 4. Second, there are strong reasons to believe that the basic permanent-transitory model, an “industry-standard” is mis-specified.

8 Conclusions

In investigating trends in cross-sectional inequality in three household surveys representative of the US population (CPS, CEX and PSID) we have encountered a number of issues deserving further study.

First, although generally in strong agreement, micro data and the aggregates from the national accounts do not line up well along two dimensions. First, per-capita consumption in the CEX displays almost none of the growth in aggregate consumption recorded in the NIPA since 1980. Second, cyclical fluctuations in pre-tax income in the CPS are twice as large as those in the NIPA. The expansion of business-cycle analysis to richer models with heterogeneous agents is at the forefront of the research program in quantitative macroeconomics. The calibration of such models requires combining aggregate and cross-sectional data. Therefore, understanding the sources of these inconsistencies is a priority.

Second, our empirical analysis of household-level inequality is only suggestive of how the wide range of insurance mechanisms available (labor supply, family, private transfers, public transfers, taxation, and financial markets) operate at different points in the distribution, and of how their respective roles have changed over the past 40 years. Future research based on structural models with heterogeneous agents and incomplete markets will give a more complete picture.

Third, our study of life-cycle inequality shows that the magnitude of growth in dispersion over the life-cycle is very sensitive to two choices: (i) whether to control for non-stationarity via cohort or time effects, and (ii) the equivalence scale used to control for life-cycle changes in family size. The rise in the age profiles for income and consumption inequality are important metrics for the persistence and insurability of income shocks. Thus more research should be devoted to disentangling cohort versus time effects, and to providing firmer theoretical foundations for the choice of household equivalence scale.

Finally, in estimating wage dynamics from the longitudinal dimension of the PSID, we argued that the standard permanent-transitory model is mis-specified: the two sets of identifying moments most commonly used in the literature yield very different parameter estimates. The natural next step in the analysis is to search for more general statistical models that can better capture the observed characteristics of wage dynamics.

A CPS

Survey description Each household in the CPS is interviewed once a month for four consecutive months one year, and again for the corresponding time period a year later: a 4-8-4 rotating panel design. However, while it is sometimes possible to follow households from one year to the next, it is not always possible to match records across consecutive years. Thus we ignore the limited panel dimension to the CPS, and treat it as a pure cross-section. Approximately 98,000 housing units were in sample for the 2007 ASEC (March CPS), of which 83,200 were determined to be eligible for interview, leading to about 76,100 interviews obtained.

There have been a succession of changes over time in the March CPS involving the sample construction, interview methods, data processing and imputation methods, weighting (reflecting new decennial Census population counts), and the structure and content of the questions themselves. More detailed questions about income were asked beginning with the 1976 survey, and the set of questions was expanded again in 1988.

For March 1988 two files are available: the regular and the rewrite file, which includes revised procedures for weighting and imputations (a previous change to the imputation procedure occurred in 1976). We use the rewrite file, which is recommended for comparison with future years. Two files are also available for 2001: including or excluding the SCHIP sample expansion. We use the smaller sample. The largest changes in the basic CPS survey methodology came in 1994, with the introduction of computer-assisted interviewing, and associated redesign of the questionnaire. Notwithstanding these and other changes, the basic structure of the March CPS has remained remarkably intact over time.

The CPS householder refers to the person, or one of the persons (the first one listed by the respondent), in whose name the housing unit is owned or rented, and is the "reference person" to whom the relationship of other household members is recorded.

Weights We use the March supplement weights to produce our estimates. Weights are chosen to make the CPS sample representative of the US population, and apply at the individual level. For household level variables, we use the household weight, which is equal to the family weight of the household reference person, which is the reference person's weight, unless the reference person is a married man in which case it is the weight of his wife. The supplement weights differ from the usual monthly CPS weights, reflecting differences in the sample, particularly the inclusion of the SCHIP subsample. For individual level variables we use individual weights, which can differ across individuals within a household because different household members have different demographic characteristics (age, sex, race, ethnicity) which are inputs to the CPS weighting procedure.

Sample selection Our basic sample selection strategy is outlined in the text: here we describe the details of how this applies to the CPS. To generate our Sample A, the cleaned version of the entire dataset, we start by dropping households that do not have a reference person, or that have more than one reference person (there are no such households from income year 1993 onwards). We then drop households in which there are household members with negative or zero weights (there are only a handful of such households from 1975 onwards). Next we drop households in which there are members with positive earnings but zero weeks worked (there are no such households from 1989 onwards). Next we drop households in which there is an individual whose hourly wage is less than half the legal minimum in that year. To apply a consistent sample selection rule across the whole sample period, we define the hourly wage here using the hours worked last week variable, which is available throughout the sample period (see below). There are no missing values for variables in the CPS, since missing values are imputed (see below). We do not exclude observations with imputed values, even if all income variables are imputed. This defines the basic "NIPA" sample used for comparison with BEA estimates of income in Figure 1.

Sample B, the starting point for measuring inequality among the population of working age households, is Sample A less all households in which there are no individuals aged between 25 and 60, inclusive. A minor difference relative to the PSID is that, since we have income data for all household members, the CPS version of Sample B retains households as long as any household member falls in the 25-60 age range, even if both the CPS reference person and their spouse fall outside the range. The CPS estimates of average hours in Figure 2 uses all individuals in Sample B.

The estimates for measures of income inequality in Figures 7-9 and 13-14 are for a subset of Sample B. In each year, we drop households with zero household earnings. Then, for each different variable of interest (e.g., unequivalized household earnings or equivalized pre-tax household income) we trim the lowest 0.5% of observations. Thus, when we apply different measures of dispersion to equivalized household earnings in Figure 8, we apply them to exactly the same set of households. In Figure 9, when we compare inequality across different measures of income, using the variance of log metric, the sample of households is the same for each measure of income, except that there is some variation in the identities of the 0.5% of households that are trimmed.

Sample C, used for statistics involving wages, is a sample of individuals from households in Sample B, aged 25-60 and with annual hours greater than 260, where annual hours are computed using hours last week prior to the 1975 income year, and using usual hours after it becomes available in 1975. Then, for 1975 onwards, we drop individuals with wages (computed using usual hours) below half the minimum (recall that Sample A applies a similar screen, but using a different measure of hours). The plots for wage dispersion over the life-cycle in Figures 13 and 14 use Sample C for the period 1975 onwards.

Hours Recall that we compute an individual's wage as annual earnings divided by annual hours worked. To compute hours worked last year we multiply weeks worked last year (wkslyr) by a measure of hours worked per week. Up to and including income year 1974 we are forced to use hours worked last week (hours), while from 1975 onwards a new variable (hrslyr) becomes available which measures usual hours per week last year. One would expect this latter measure to produce a much more accurate estimate for an individual's annual hours, and thus for his annual wage. We compute hours and wages both ways for the 1975-2005 period. Reassuringly, we find that trends in the variances of hours and wages are very similar over this period, while there is some difference, unsurprisingly, in levels of inequality - there is less variance in wages using the better measure. We also find a very similar increase in the correlation between individual hours and individual wages using the two different approaches, though the level of the correlation is much lower using the hours-last-week question. This reflects the well-known division bias: mis-measurement in hours translates automatically to mis-measurement in the inverse direction in wages, and thus drives down the observed wage-hour correlation.

Prior to 1975 income year, in addition to having to use hours last week (rather than usual weekly hours) there is a second reason why our measure of hours is of lessor quality, which is that the March CPS data files record weeks worked in intervals rather than as specific integers (even though the original questionnaires for the 1970-1975 survey years asked for integer responses). Based on the weeks worked distributions in income years 1975 forwards, Unicon converts interval codes into estimates of cell means. We compute an individual's wage as individual earnings divided by hours last week times estimated-cell-mean weeks worked.

Taken together, measures of hours and wages prior to income year 1975 are more uncertain than in later years, and estimates of first and second moments for this period should be viewed accordingly.

Imputation The CPS is subject to two sources of nonresponse: noninterview households and item nonresponse. To compensate for this data loss, the weights on noninterviewed households are distributed among interviewed households. The second source is item nonresponse, meaning a respondent either does not know or refuses to provide the answer to a question. The Census Bureau imputes missing income data using a "hot deck" procedure which matches individuals with missing observations to others with similar demographic and economic information who did answer the questions. For example, the weekly earnings hot deck is defined by age, race, sex, usual hours, occupation and educational attainment. Before any edits are applied, the data is sorted geographically so that missing values are allocated from geographically close records.

We do not exclude households with imputed income because imputation is widely-used, especially for asset income categories. Thus dropping households with imputed values would drastically reduce the sample size, and call into question the appropriateness of the CPS-provided weights. Response rates for the CPS are high relative to other large household surveys, but have been declining over time. Moreover, for households nonresponse rates are higher for income than for other kinds of questions. Atrostic and Kalenkoski (2002) report response rates, defined as percent of all recipients (reported and imputed) who also reported an amount for the 1990 March CPS and the 2000 March CPS. Response rates for earnings from longest job (incer1) fell from 81.2 percent to 72.4 percent. Response rates for interest and dividend income fell from over 70 percent to below 50%. In terms of the share of income imputed, 26.8 percent of total wage and salary earnings, 43.8 percent of non-farm self-employment income, and 64.1 percent of interest and dividend income was imputed in 2000. For a significant fraction of households all income items are imputed.

Topcoding Topcoding is an important issue to address in the CPS, both for computing means, and for measuring the evolution of inequality at the top of the income distribution. Public top-code thresholds vary widely across income categories, and across time. An additional problem is that the Census Bureau's internal data is also subject to censoring (to economize on computer tape, and to protect against gross errors). For example, the public use censoring point for the variable incwag (income from wages and salaries) was $50,000 for the income years 1975-1980, $75,000 for 1981-1983 and $99,999 for 1984-1986. For the same variable, the internal CPS censoring points were $99,999 for the period 1975-1984, and $250,000 for 1985-1986.

We deal with top-coded observations by assuming the underlying distribution for each component of income is Pareto, and we follow a suggestion of David Domeij by forecasting the mean value for top-coded observations by extrapolating a Pareto density fitted to the non-top-coded upper end of the observed distribution. This procedure automatically takes care of the internal censoring problem, since the internal threshold always exceeds the public use limit. It also has the advantage that in principle it adjusts appropriately to changes in top code thresholds.

We apply this procedure at the most disaggregated decomposition of income possible. Thus, for example, for each year we divide the set of observations for the variable incer1 (income from primary source) according to whether or not they are flagged as wage and salary or self employment, and run separate regressions on the two sets of observations. This is important for two reasons. First, for any given individual, while one type of income may be top-coded others will not be. Second, there is more upper tail concentration in some types of income than others.

Beginning in income year 1995 the CPS started reporting cell means for top-coded observations, with cells identified by gender, race and work experience. This allows us to assess the performance of the regression procedure. We find that the regression approach generally performs very well for most income categories. It leads us to slightly over-predict income from primary source flagged as wages and salary over the 1995-2005 income year period, and to slightly under-predict interest income.

Since our primary goal is to measure changes in inequality consistently over time, we use the regression approach for the primary income variable through the sample period, even when cell means are available. However, at the same time that the Census began reporting cell means, they drastically reduced public use censoring points for many income categories: the threshold for interest income declined from $99,999 to $35,000 between income years 1997 and 1998 and to $25,000 in 2002, while the threshold for dividend income declined from $99,999 to $15,000. We found that when the distribution is truncated too far to the left, the Pareto-extrapolation procedure does not always perform well. Thus for income years 1998 to 2005 we use cell means for all income categories, except income from primary source. Unfortunately, switching from regression-based adjustment to cell means has the effect of reducing measured concentration at the top of the distribution of asset income. We therefore make an adjustment in Figure 11 to our post-1998 estimates for Gini coefficients for income categories that include asset income. The adjustment factor is the ratio of the Gini coefficient in 1997 that emerges when top-coded observations are adjusted using the regression procedure, and the Gini coefficient for 1997 that emerges when we apply the 1998 top-code thresholds and reported cell means for asset income to the 1997 data.

Comparing our per-capita salary estimates, derived using the cell means, to figures made publicly available by the CPS (http://www.census.gov/hhes/www/income/dinctabs.html), the differences are tiny: less than \$50 in all income years between 1995 and 2005, except 1999, where our estimate is \$383 below the public number. However, there are errors in the reported cell means for earnings for the 2000 survey year (1999 income year): for example, the replacement value for earnings (topcode value \$150,000) for male, non-black non-hispanic full-year full-time workers falls from \$306,731 in 1999 to \$229,340 in 2000, and then rises to \$335,115 in 2001. Larrimore et. al. (2008) were granted access to internal CPS data, and report a 2000 cell mean for this group of \$300,974.

The precise procedure we follow to compute top-coding adjustments is as follows. First, for a particular income variable, we identify the existence of top-coded observations. Then we sort observations in ascending order by income. The sample for our least-squares regression is the top (weighted) decile of non-zero, non-top-coded observations. For each individual i with income y_i we compute the fraction of households in our sample (including top coded households) with income greater than y_i, which we denote v_i. We then regress $\ln(v)$ on a constant and $\ln(y)$, and set the adjustment factor to $\beta/(1+\beta)$, where β is the estimated coefficient on income. For a given income type in a given year, all top coded observations are assigned an income value equal to the top-code threshold times this adjustment factor.

Demographic variables First we note that demographic variables (age, years of education, etc) refer to the survey year, while questions about income refer to the previous year. We do not attempt to adjust for this timing discrepancy. Thus, for example, the CPS version of Sample B for income year 1980 corresponds to households who in March 1981 reported at least one households member aged 25-60.

Head If there are any 25-60 year-old males in the household, the oldest male is the head. If there are no such males, the oldest 25-60 year-old female is the head. Note that this definition of head makes no connection to the identity of the CPS reference person. *Education* We define an individual to be college educated if they have 16 years of schooling or more. *Race* We divide individuals into those identifying as “white” and those that do not, who we label “non-white”. Until 1988 the only non-white options were “black” or “other”. In 1988, American Indian and

Asian were added as additional options. In 1996 the "other" option was dropped. In 2003 many new options were added.

Dispersion related to observables, and residual inequality For the plots of residual dispersion in Figures 5 and 7 we proceed as follows.

The sample for Figure 7 is in Sample B in which there are either one or two adults (a head and non-head) aged 25-60. These households constitute around 96% of all households in Sample B. The sample for Figure 5 is the subset of these households with a male head (where head is defined above).

Both sets of regressions use exactly the same set of regressors. The independent variables for the two-adult households are: 3 race dummies (white-white, non-white-non-white, mixed-race), 2 sex dummies (male-female, same-sex), 4 education dummies (college-college, college-non-coll, non-coll-college, non-coll-non-coll), average years of education for all adults, a quadratic in age (actual age minus 25) for the head, a quadratic in age for the non-head, number of household members below age 25, number of members above age 60. Note that this specification admits the possibility that earnings in households in which only the head has a college degree (college/non-college) might differ from those in which only the non-head has a degree (non-college/college). Note also that by construction there are no female/male households. The independent variables for the one-adult households are analogous: 2 race dummies, 2 sex dummies, 2 education dummies, years of education, a quadratic in age, number below age 25, number above age 60.

Income measures Over our sample period there have been two important changes in the set of income questions asked in the March CPS, one beginning in the 1975 income year, and a second in the 1987 income year. However, these changes appear to have a negligible impact on either total income, or its division between different classes of income. The exception to this is for private transfers, which increases from 1.9 percent of pre-tax income in 1974 to 3.5 percent in 1975 (where these figures apply to Sample A).

Labor Income

1967-1986 incwag

1987-2005 incer1 (if ernsrc=1 (wage and salary)) + incwg1

incwag = income from wage and salary; incer1 = earnings from longest job before deductions; incwg1 = income from other wage and salary

Self Employment Income

1967-1986 incse + incfrm

1987-2005 incer1 (if ernsrc=2 or 3 (farm or non-farm self-employment)) + incse1 + incfr1

incse = income from non-farm self-employment; incfrm = income from farm or nonincorporated self-employment; inse1 = income from other work – own business self-employment; incfr1 = income from other work – farm self-employment

Earnings labor income + 2/3 self-employment income

Private Transfers

1967-1974 incoth

1975-1986 incret + incalc + incoth

1987-2005 incoth + incalm + inchld + incds1 + incds2 + incont + incrt1 + incrt2 + incsi1 + incsi2

incoth = income from other sources; incret = income from retirement funds; incalc = income from alimony and child support; incalm = income from alimony; inchld = income from child support; incds1 = income from disability income – primary source; incds2 = income from disability income – secondary source; incont = income from contributions, assistance from friends; incrt1 = income from retirement income – primary source; incrt2 = income from retirement income – secondary source; incsi1 = income from survivors income – primary source; incsi2 = income from survivors income - secondary source

Earnings Plus earnings + private transfers

Net Asset Income

1967-1974 incint

1975-1986 incint + incdiv

1987-2005 incint + incdv2 + incrnt

incint = income from interest, dividends and net rentals; incdiv = income from dividends, rents and trusts; incdv2 = income from dividends; incrnt = income from rent

Pre-Government Income earnings plus + net asset income

Public Transfers

1967-1974 incpa + incomp + incss

1975-1986 incpa + incomp + incss + incsec

1987-2005 incpa + incss + incsec + inced + incvet + incwcp + incuc

incpa = income from public assistance or welfare; incomp = income from unemplymt/workers comp/veterans payments/govt pensions; incss = income from social security or railroad retirement – from US govt; incsec = income from supplemental security; inced = income from educational assistance; incvet = income from veterans payments; incwcp = income from worker's compensation; incuc = income from unemployment compensation

Pre-Tax Income pre-government income + public transfers

Taxes (imputed)

1979-2005 fedtaxbc + statetaxbc + fica - eitcrd

fedtaxbc = federal income tax liability, before credits; statetaxbc = state income tax liability, before credits; fica = social security retirement payroll deduction; eitcrd = earned income tax credit

Given the various income components described above, the different measures of income used in the paper are constructed successively as follows, following the project guidelines:

Disposable Income pre-tax income - taxes

Household-level measures of income are constructed by adding up the income of all household members

B PSID

Definition of "head" The head of the family unit (FU) must be at least 16 years old, and the person with the most financial responsibility in the FU. If this person is female and she has a husband in the FU, then he is designated as head. If she has a boyfriend with whom she has been living for at least one year, then he is head. However, if she has 1) a husband or a boyfriend who is incapacitated and unable to fulfill the functions of head, 2) a boyfriend who has been living in the FU for less than a year, 3) no husband/boyfriend, then the FU will have a female head. A new head is selected if last year's head moved out of the household unit, died or became incapacitated, or if a single female head has gotten married. Also, if the family is a split-off family (hence a new family unit in the sample), then a new head is chosen.

Samples In addition to the SRC sample, described in the main text, the second sample which belonged to the original 1968 survey is part of the Survey of Economic Opportunity (SEO) which was conducted by the Bureau of the Census for the Office of Economic Opportunity. The PSID selected about 2,000 low-income families with heads under the age of sixty from SEO respondents. In 1997, the SEO sample was reduced by one half.

In 1990, PSID added 2,000 Latino households, including families originally from Mexico, Puerto Rico, and Cuba. While this sample (the so called "Latino sample") did represent three major groups of immigrants, it missed out on the full range of post-1968 immigrants, Asians in particular. Because of this crucial shortcoming, and a lack of sufficient funding, the Latino sample was dropped after 1995. A sample of 441 immigrant families, including Asians, was added in 1997 (the so called "Immigrant sample").[46]

File structure of the PSID data Information on family-level variables and on individual-level variables (for individuals in families belonging to the PSID sample) are split in two different sets of files. There are several family-level files, one for each year (*Single-year Family Files*), which contain one record for each family interviewed in the specified year. Individual income measures, and a large set of other individual-level variables (e.g., race, marital status) are contained in the *family files*. There is only one cross-year individual file with some individual-level data (e.g. education) collected from 1968 to the most recent interviewing wave (*Cross-year Individual File*). The file also contains the ID of the family with whom the person is associated in each year, which can be used to match individual-level data and family-level data.

The PSID contains many useful data supplements. The *Family Income-Plus Files, 1994-2001* contain various constructed income variables for household income and its components. The *Hours of Work and Wage Files, 1994-2001* contain constructed variables for total annual hours worked of heads and wives. The *Wealth Supplement File* includes detailed wealth information for 1984, 1989, 1994, 1999, 2001, 2003, and 2005. It can be linked to the rest of PSID data. Finally, a *Validation Study* was designed to assess the quality of economic data obtained in the PSID. The first wave of the Validation Study was conducted in 1983 and a second wave was conducted in 1987. For the Validation Study, the standard PSID questionnaire was administered to a sample drawn from a single large manufacturing firm. Questionnaire results were compared to company records to verify respondents' answers to questions such as earnings and hours worked. This source of data has been frequently used in the past to assess the size of measurement error in earnings and hours.

Data quality. Traditionally the PSID data has been released in two stages –an *early release* file with variables named ERxxxxx, and a *final release* file with variables named Vxxxx. The final release file contains data that has been subject to more stringent cleaning and checking

[46] The so called "PSID core sample" combines the SRC, SEO and Immigrant samples. If one plans to combine these three samples together, weights should be used.

processes and contains a number of constructed variables (e.g., total annual labor income of the head and wife). From 1994 on the final release files have not been made available. Instead, clean variables for labor income, annual hours and several other variables, are available in some of the supplementary data sets. These include the *Family Income-Plus Files* which contain various constructed income variables, the *Hours of Work and Wage Files*, which are used for data on annual hours worked.

Top coding and bracketed variables. We deal with top-coded observations by assuming the underlying distribution for each component of income is Pareto, and by forecasting the mean value for top-coded observations by extrapolating a Pareto density fitted to the non-top-coded upper end of the observed distribution. Variables with top-coded observations for which this imputation procedure was used are marked in Table A.

In some of the early waves, a number of income measures were bracketed. For these variables, we use the midpoint of each bracket, and 1.5$\times$ the top-coded thresholds for observations in the top bracket. Bracketed variables are marked in Table A.

Variable Definitions. In the PSID all the questions are retrospective, i.e. variables in survey-year t refer to calendar year $t-1$. The interview is usually conducted around March. A complete listing of the original PSID variables used in the construction of the variables in the final data set, year by year, can be found in Table A. When variables were not defined consistently across years (for example race was categorized differently in different years), the variables were recoded based on their original (and less detailed) coding, so as to be consistent across years.

A detailed definition of the key variables used in the study follows below:

Earnings. For heads and wives, annual earnings includes all income from wages, salaries, commissions, bonuses, overtime and the labor part of self-employment income. The PSID splits self-employment income into asset and labor components using a 50-50 rule.

Annual Hours of Work. For heads and wives, it is defined as the sum of annual hours worked on the main job, on extra jobs, plus annual hours of overtime. It is computed by the PSID using information on usual hours worked per week and the number of actual weeks worked in the last year.

Hourly Wage. It is defined as Earnings divided Annual Hours of Work.

Household Earnings. It is defined as the sum of head and wife Earnings.

Household Earnings Plus. It is defined as Household Earnings plus private transfers. Private transfers include alimony, child support, help from relatives, miscellaneous transfers, private retirement income, annuities and other retirement income.

Financial Asset Income. It includes income from interests, dividends, trust funds, and the asset part of self-employment income.

Total Asset Income. It includes Financial Asset Income plus rental income. We do not include an imputed rental value for owner-occupied housing in the definition of rental income.

Household Pre-Government Income. It is the sum of Household Earnings Plus and Total Asset Income

Household Pre Tax-Income. It is the sum of Household Pre-Government Income plus public transfers. Public transfers include payments from the Aid to Families with Dependent Children (AFDC) program, Supplemental Security Income payments, other welfare receipts, plus social security benefits, unemployment benefits, worker's compensation and veterans' pensions. In the 1968 and 1969 interview years, many items are missing, so we start computing this measure from the 1970 survey (actual year 1969).

Taxes. An estimate of household federal income taxes, and state income taxes is computed based on the NBER's TAXSIM program.

Household Disposable Income. It is constructed as the sum of Household Pre-Government Income plus public transfers less federal and state taxes.

Food Consumption. It is defined as total expenditures on food eaten at home, on food eaten out of home, on food delivered, and on food purchased using food stamps. There is no food data available in the 1973, 1988 and 1989 interview years, except for food purchased using food stamps, so we omit those years in all calculations using this variable.

C CEX

Our data come from the CEX Interview Surveys 1980 through 2006 provided by the Bureau of Labor Statistics (BLS). Consumption expenditure data are from the Family Characteristics and Income (FAMILY) files except for the years 1982 and 1983, for which the FAMILY files do not contain consumption information. For those years consumption data are from the Detailed Expenditures (MTAB) files. Consumption data for those years is fully consistent with consumption data for other years as consumption reported in the FAMILY files is just an aggregation of the information in the MTAB files. Income data are from the FAMILY files and hours worked by household members (also used to construct wages) are from the Member Characteristics and Income (MEMBER) files.

Sample size. The total sample size for the CEX is reported in table 1 above. The sample size is not uniform across years as in 1999 there has been a major sample increase. Our basic sample (sample A) has an average size of around 15500 observations per year during the period 1980-1998, and its size increases to around 22800 observations per year in the period 1999-2006.

Definition of "head" We define household head the oldest male aged between 25 and 60. If there are no such males in the household we define the head as the oldest female aged 25-60. If there is no such females the head is not defined (the household is not included in sample B).

Non durable consumption expenditures. The definition of non durable consumption expenditures used in figures 12 and 13 includes the following categories: food and beverages (including food away from home and alcoholic beverages), tobacco, apparel and services, personal care, gasoline, public transportation, household operation, medical care, entertainment, reading material and education. Each observation is constructed by adding up household nominal expenditures in these categories during the three months period preceding the interview and then deflating the total using the CPI-U for that period. A change in survey methodology (see Battistin, 2003, for details) causes a sizeable (about 15%) systematic downward bias in reported food expenditures for all the observations in the years 1982–1987. In order to correct for this bias, we regress the log of food expenditures for all years on a quadratic time trend, on quadratics in income and total nonfood consumption expenditures, on weeks worked, on a complete set of household characteristics (including age, education, region of residence, and family composition), on a dummy for the period 1982–1987, and on the interactions term of the dummy with all other independent variables. We then use the regression coefficients to scale up food expenditures for every observation in the period 1982–1987.

Wages, earnings and disposable income Earnings of each household member are computed as the sum of wages and salaries plus two thirds of business and farm income earned by that member. Hours worked by each member are computed as number of weeks worked during the year times the number of hours per week usually worked by that member. Wages are computed as earnings divided by hours. Household earnings are the sum of earnings of each household member. Household disposable income includes the sum of wages, salaries, business and farm income earned by each member plus household financial income (including interest, dividends and rents) plus private transfers (including private pensions, alimony and child support) plus public transfers (including social security, unemployment compensation, welfare and food stamps) minus total taxes paid (including federal, state, local and social security contribution).

Imputation Until 2004 the CEX did not use imputation methods to derive income for non responses.. For the years 2004 and 2005 income imputation is used and it is not always possible to select out only observations with non imputed measures. In 2006 more information is provided in the survey and thus it is possible to select only observations with non imputed measures. For consistency, when possible, we use only observations with non imputed measures.

Top coding. Only a very limited number of consumption categories are subject to topcoding. In particular within non-durable consumption expenditures only some categories of medical spending (such as hospital services) are subject to top coding. We do not attempt to correct for it and we simply use the value reported by the CEX (the value is equal to the topcoding threshold before 1996 and equal to the mean of the topcoded observations after 1996). Topcoding in earnings is potentially more important as the fraction of topcoded earnings observations in some year can reach 2% of the sample. Also public topcoding thresholds vary across income categories, and across time. We deal with top-coded observations in the CEX following a procedure as close as possible to the one followed in CPS. We assume that the underlying distribution for each component of income is Pareto, and we forecast the mean value for top-coded observations by extrapolating a Pareto density fitted to the non-top-coded upper end of the observed distribution. This procedure automatically adjusts appropriately to changes in top code thresholds.

We apply this procedure separately to the three components of individual earnings (salary, business income and farm income). Some components of disposable income (such dividends or interests) are also subject to topcoding but, since the fraction of top-coded observations never exceeds 0.1% of the sample, we simply use the value reported by the CEX (the value is equal to the topcoding threshold before 1996 and equal to the mean of the topcoded observation after 1996).

Time aggregation We assign an observation to a given year if the interview is completed in that year.

Weighting All annual aggregate consumption measures (figure 3) are computed using weighted data from annual cross sections.. All annual consumption inequality measures are computed using unweighted data from annual cross sections. Inequality measures are basically not affected by weighting.

Non overlapping income and consumption As mentioned in the main text a given household is interviewed in the CEX a maximum number of 4 consecutive quarters. Each quarter the household members is asked to report consumption expenditures information but income questions are only asked to the households during the first and fourth interview. So income information reported for households in the 2nd and 3rd interview is the same as the one reported in the first interview. This implies that for roughly half of our CEX observations income and consumption do not refer to an overlapping period. In order to assess whether this issue affects the relation between income and consumption inequality (figures 12 and 13) we constructed a sample where we selected only households that are in the CEX for all 4 interviews and we constructed consumption as the sun of consumption over all 4 interviews and used income in the last interview. In this case the measures of income and consumption fully overlap. Results for the alternative sample are very similar to our basic sample (the only difference is that the alternative sample is more volatile over time as the sample size is significantly smaller)

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	PSID (1967-96, 98, 00, 02)		CPS (1967-2005)		CEX (1980-2006)	
	dropped	remaining	dropped	remaining	dropped	remaining
Initial Sample		**123,788**		**2,217,997**		**638,237**
Missing/miscoded household info$^{(a)}$	21,295	102,491	8,993	2,209,004	104,302	533,935
Implausible consumption$^{(b)}$					2,723	531,212
Pos. labor inc. & zero hours	309	102,182	17,599	2,191,405	179	531,033
Wage <0.5*minimum wage	4,675	97,507	121,367	2,070,038	47,046	483,987
Sample A		**97,507**		**2,070,038**		**483,987**
Head aged 25-60	18,774	78,733	524,609	1,545,429	137,356	346,631
Sample B		**78,733**		**1,545,429**		**346,631**
Total individuals aged 25-60 in sample B$^{(c)}$		136,896		2,578,035		552683
Individuals aged 25-60 with hours>260	40,997	95,899	599,544	1,978,491	97,574	455,109
Sample C		**95,899**		**1,978,491**		**455,109**

(a) In the CEX this category includes households classified as incomplete income respondents

(b) In the CEX this category includes households which report non-positive total consumption expenditure (67), households which report non-positive expenditures on non-food consumption (118), and households which report quarterly expenditures on food of less than $100 in 2000 $ (2,538)

(c) In the PSID individuals are only either heads or wives

Table 1: Sample selection in the PSID, the CPS and the CEX.

	1967-1979		1980-1989			1990-1999			>=2000		
	PSID	CPS	PSID	CPS	CEX	PSID	CPS	CEX	PSID	CPS	CEX
Avg. household size	3.32	3.33	2.98	2.98	2.99	2.89	2.89	2.88	2.77	2.82	2.86
% households with spouse	77.9	72.0	73.1	62.2	62.5	69.0	57.4	58.2	67.3	54.9	56.7
Avg. male age	41.2	41.0	39.7	39.7	39.4	40.9	40.3	40.3	42.1	41.7	41.9
Avg. female age	39.1	41.3	37.9	40.0	39.6	39.3	40.6	40.2	40.7	42.0	41.9
% white male	90.0	89.3	91.9	86.8	87.5	91.7	84.5	86.8	90.1	82.5	84.3
% male $\geq$16 years edu	23.0	19.4	30.2	26.0	27.8	32.9	28.0	31.3	31.9	30.2	31.0
% female $\geq$16 years edu	13.8	11.9	22.2	19.1	19.1	26.8	24.6	26.1	28.2	29.8	29.2

Table 2: Demographic characteristics of sample B in PSID, CPS and CEX.

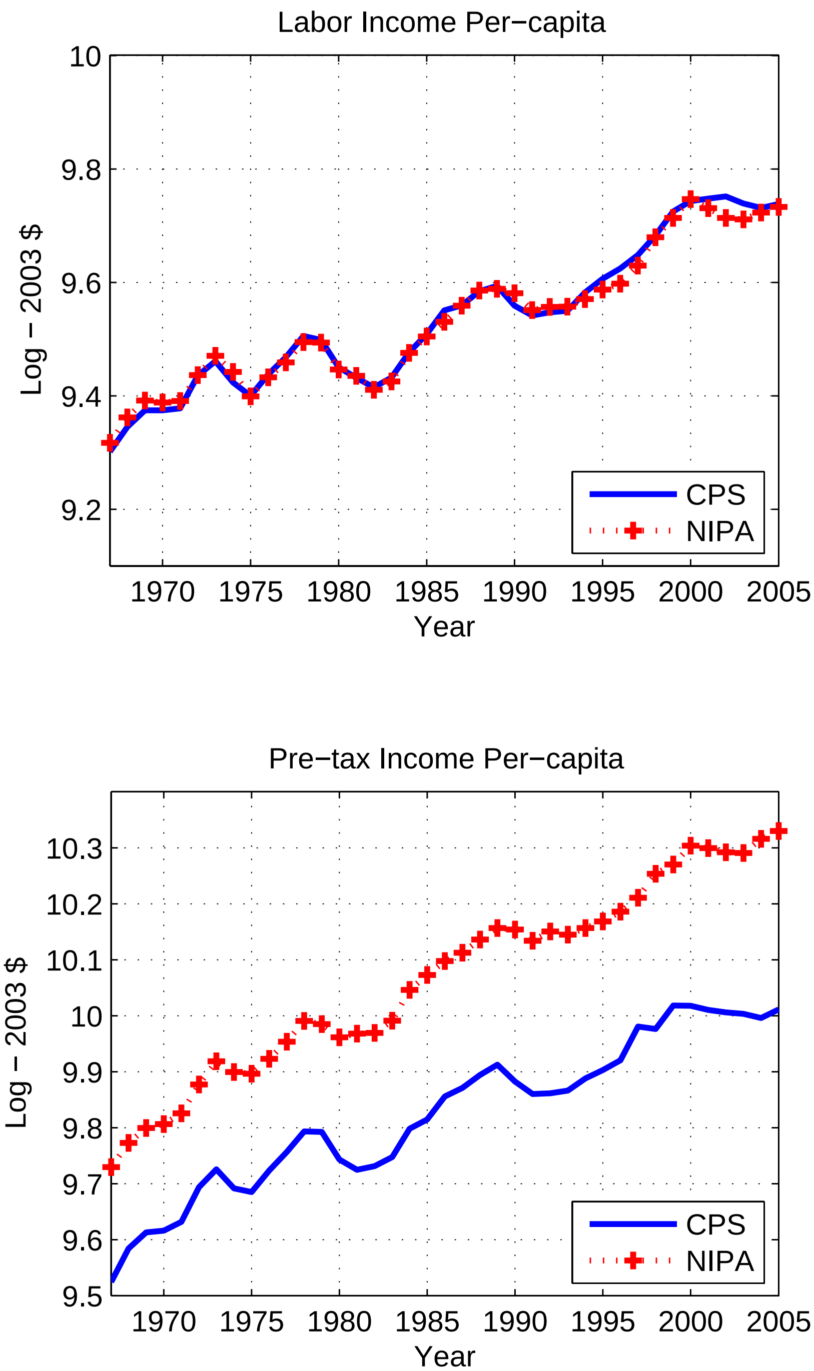

Figure 1: Comparison between per-capita averages in CPS and NIPA: labor income and pre-tax income

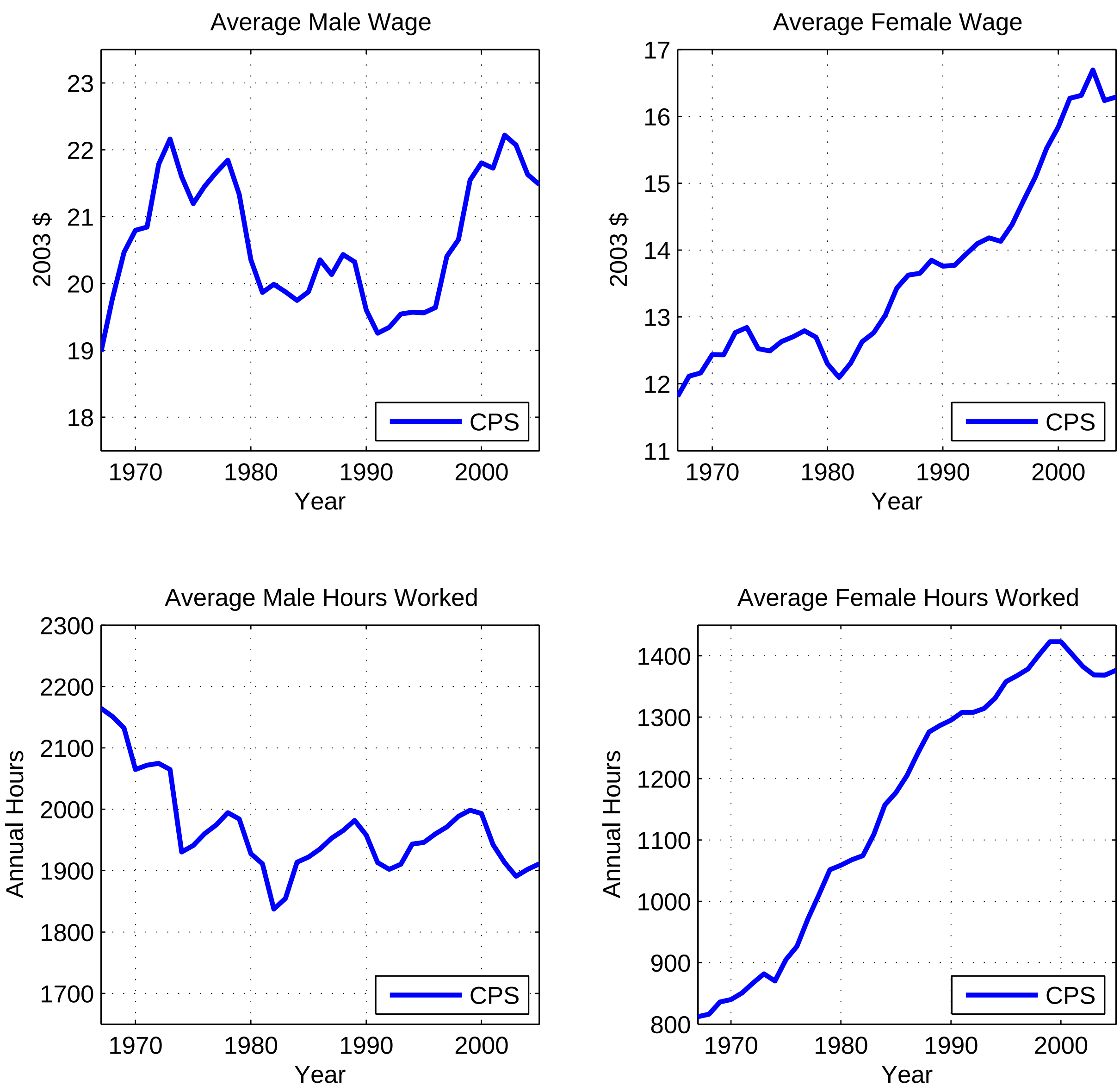

Figure 2: Average wages and hours worked by gender

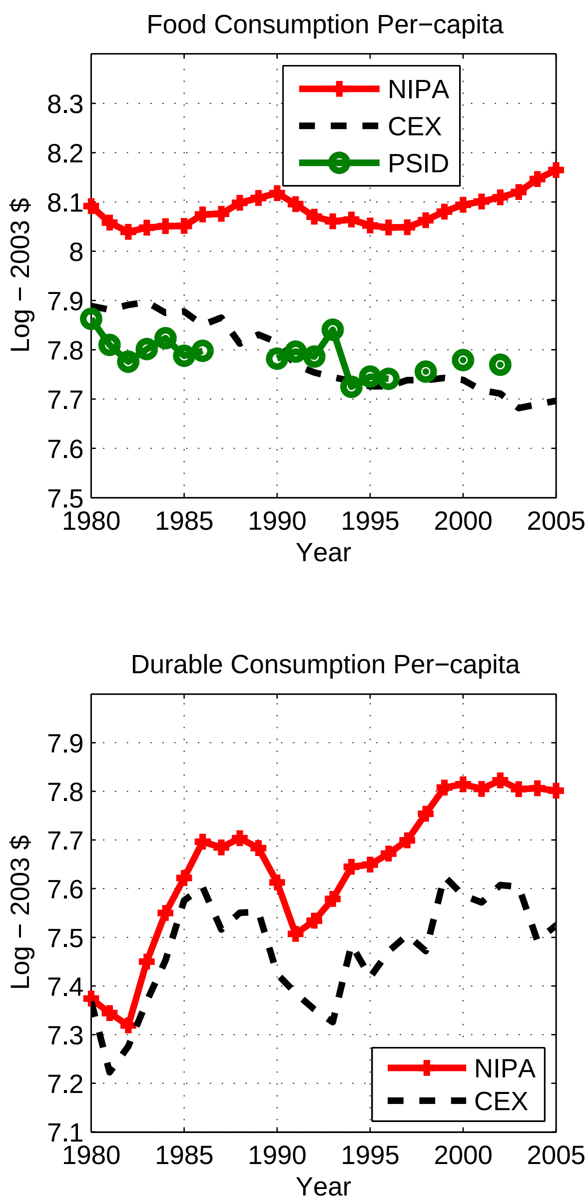

Figure 3: Comparison between per-capita averages in CEX and NIPA: various definitions of consumption

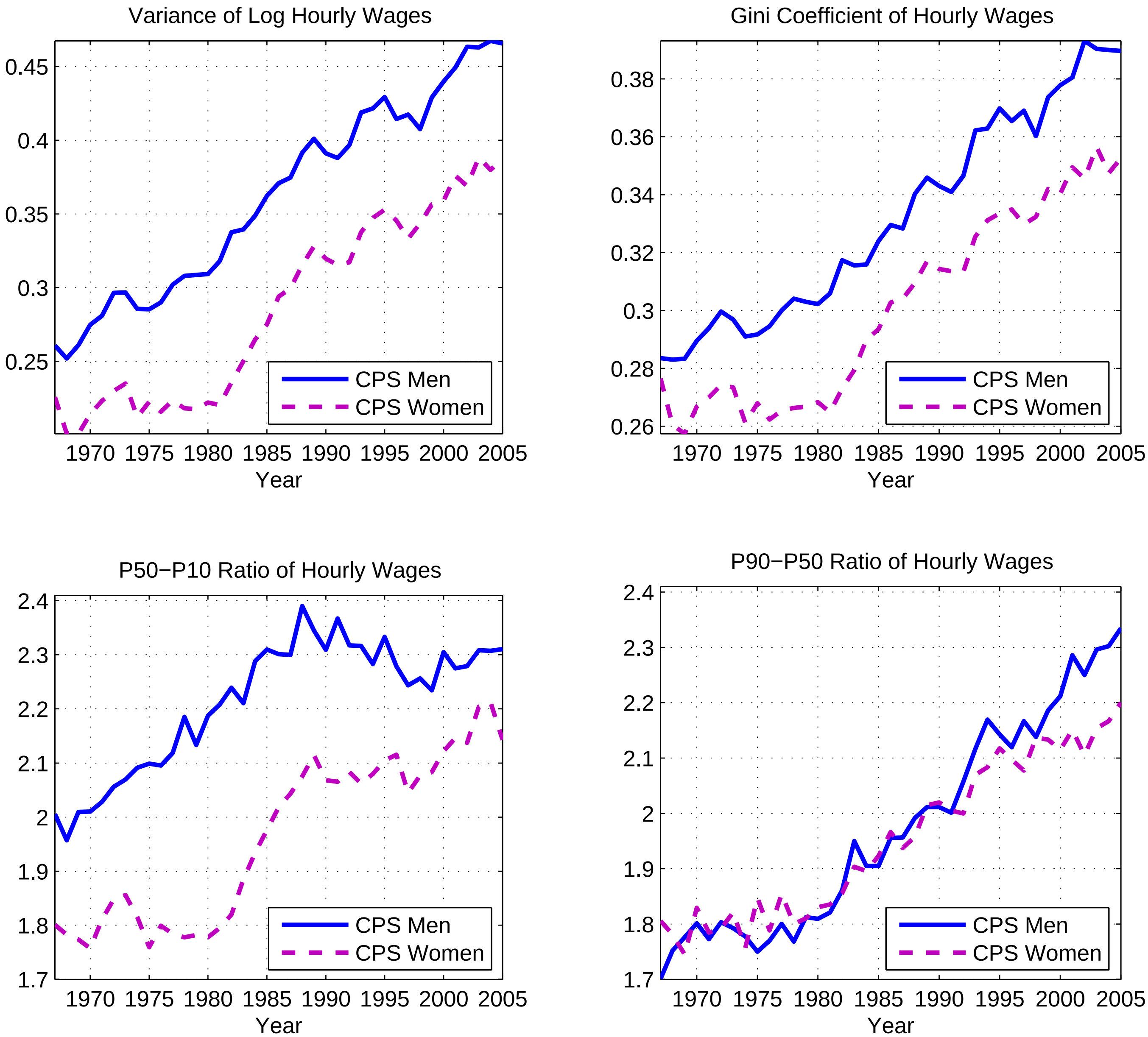

Figure 4: Wage inequality

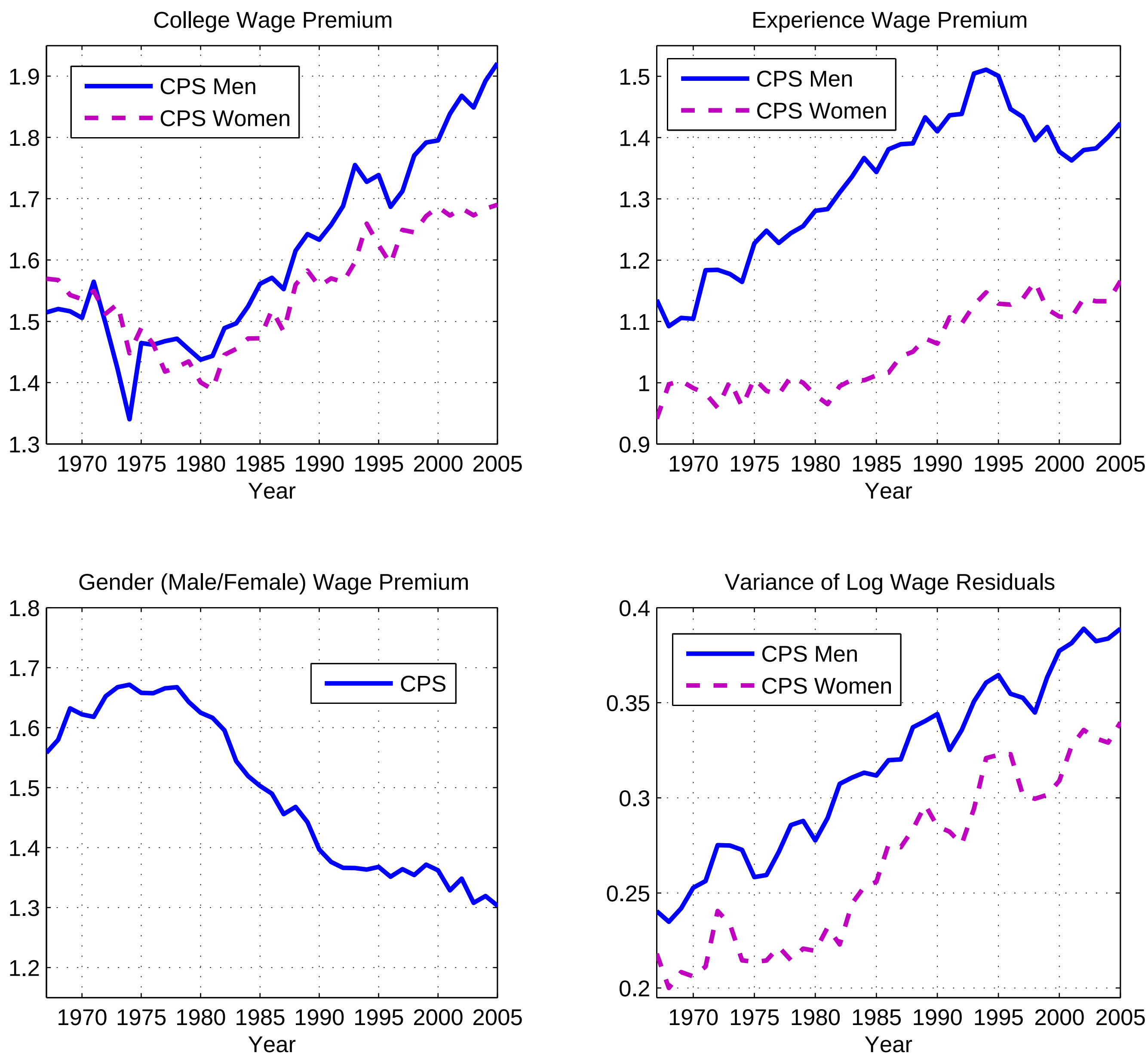

Figure 5: Education, experience and gender wage premia and residual wage inequality

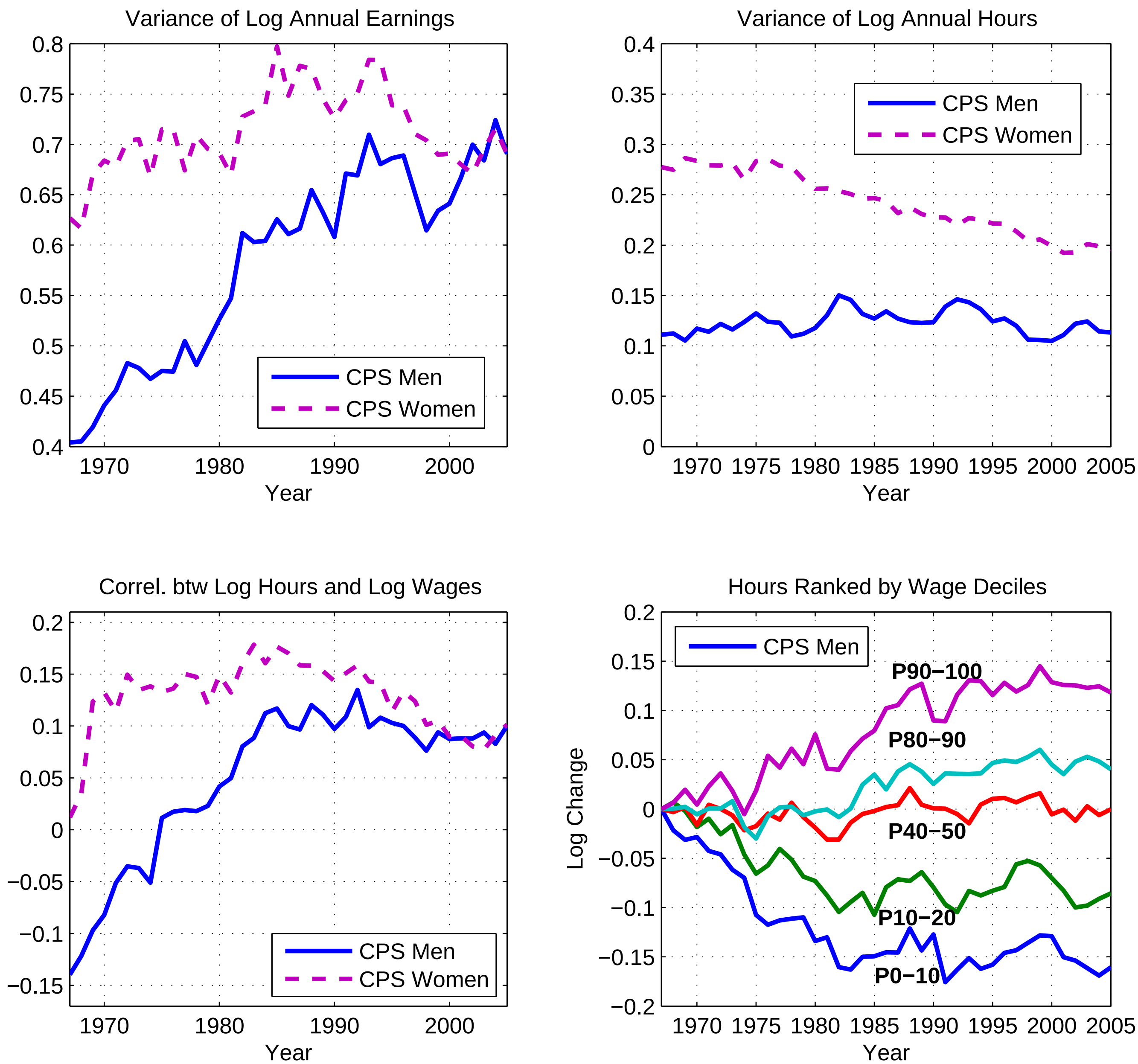

Figure 6: From wage inequality to earnings inequality

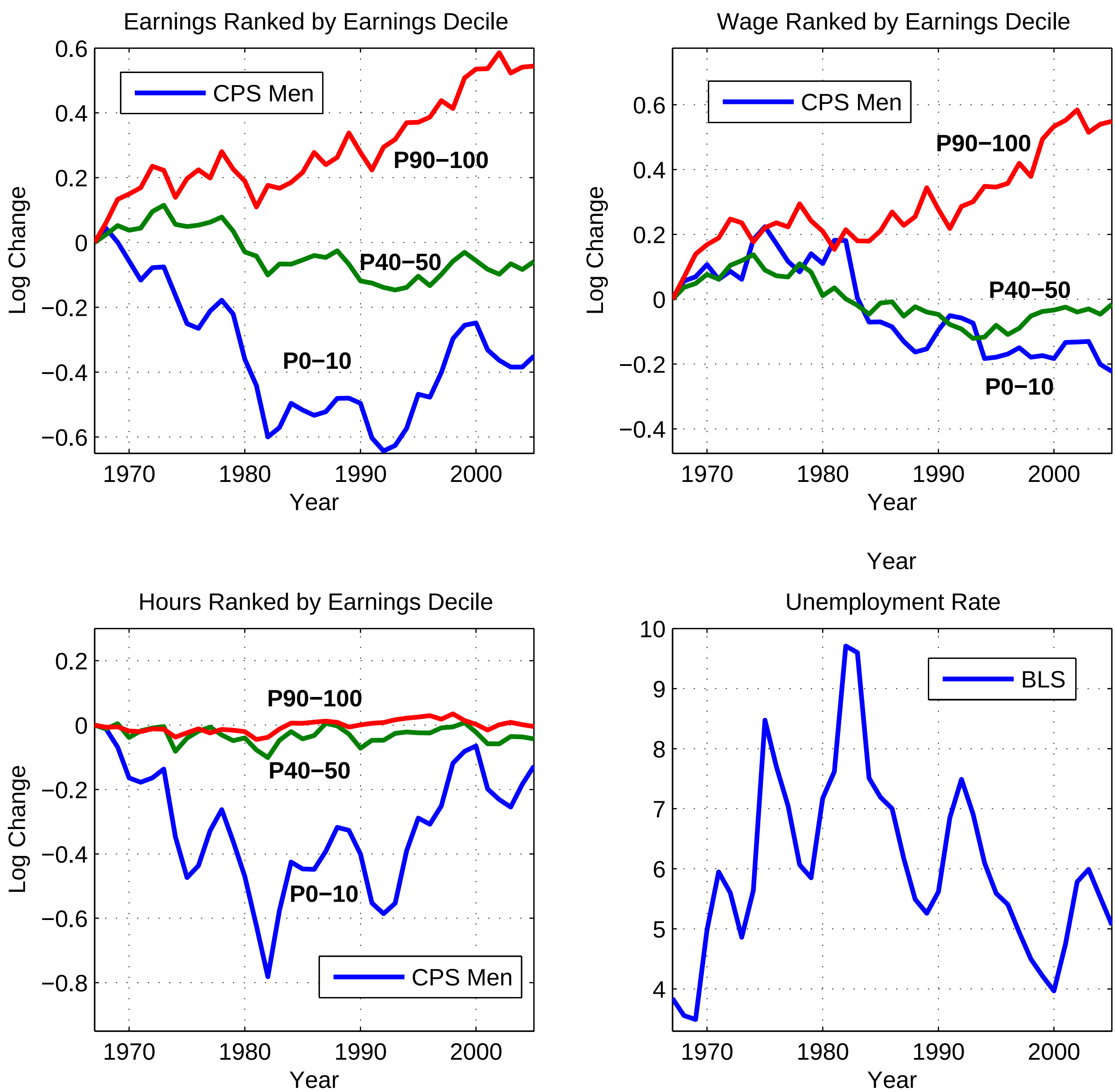

Figure 7: Understanding the dynamics of male earnings inequality

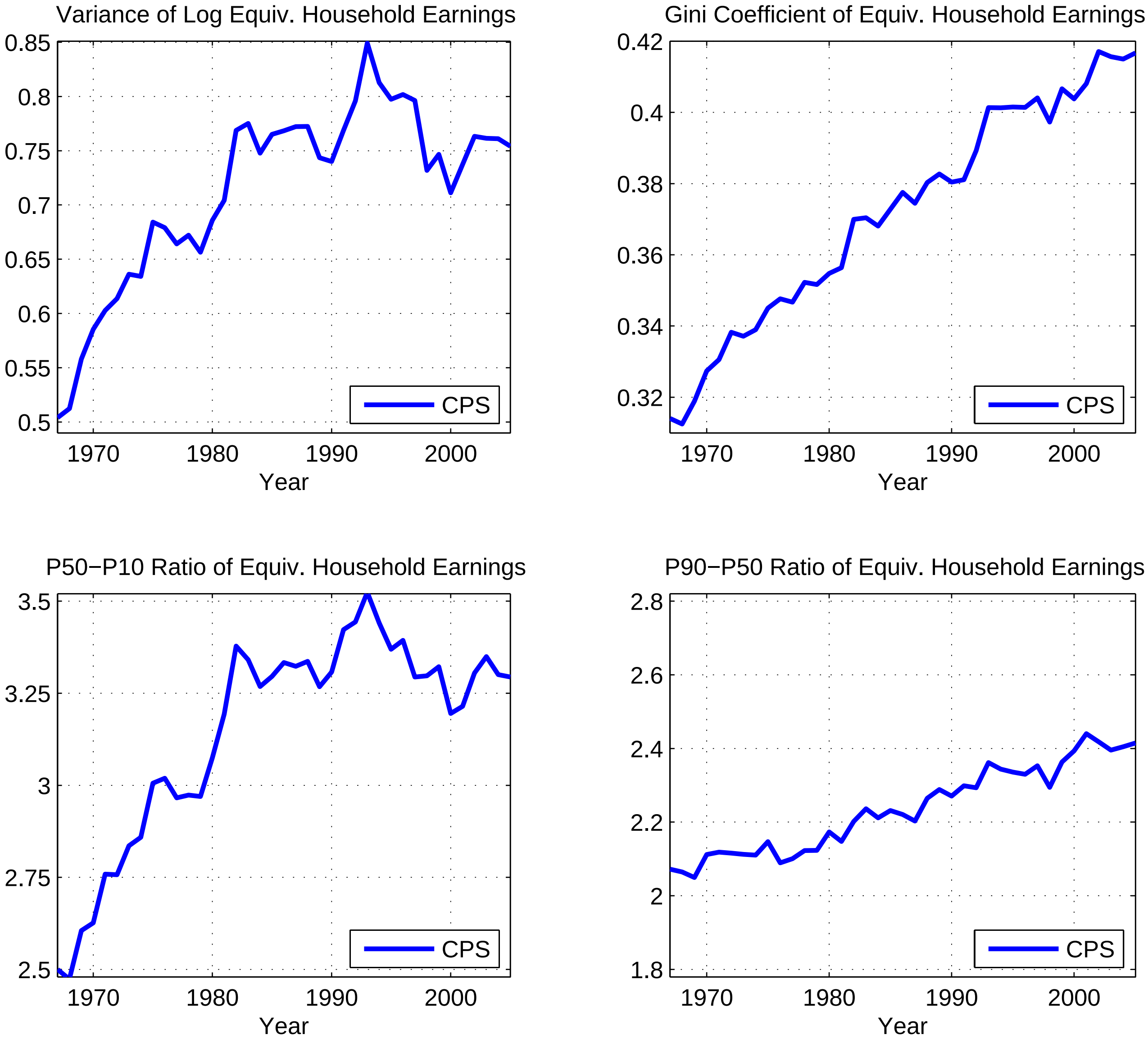

Figure 8: Household earnings inequality

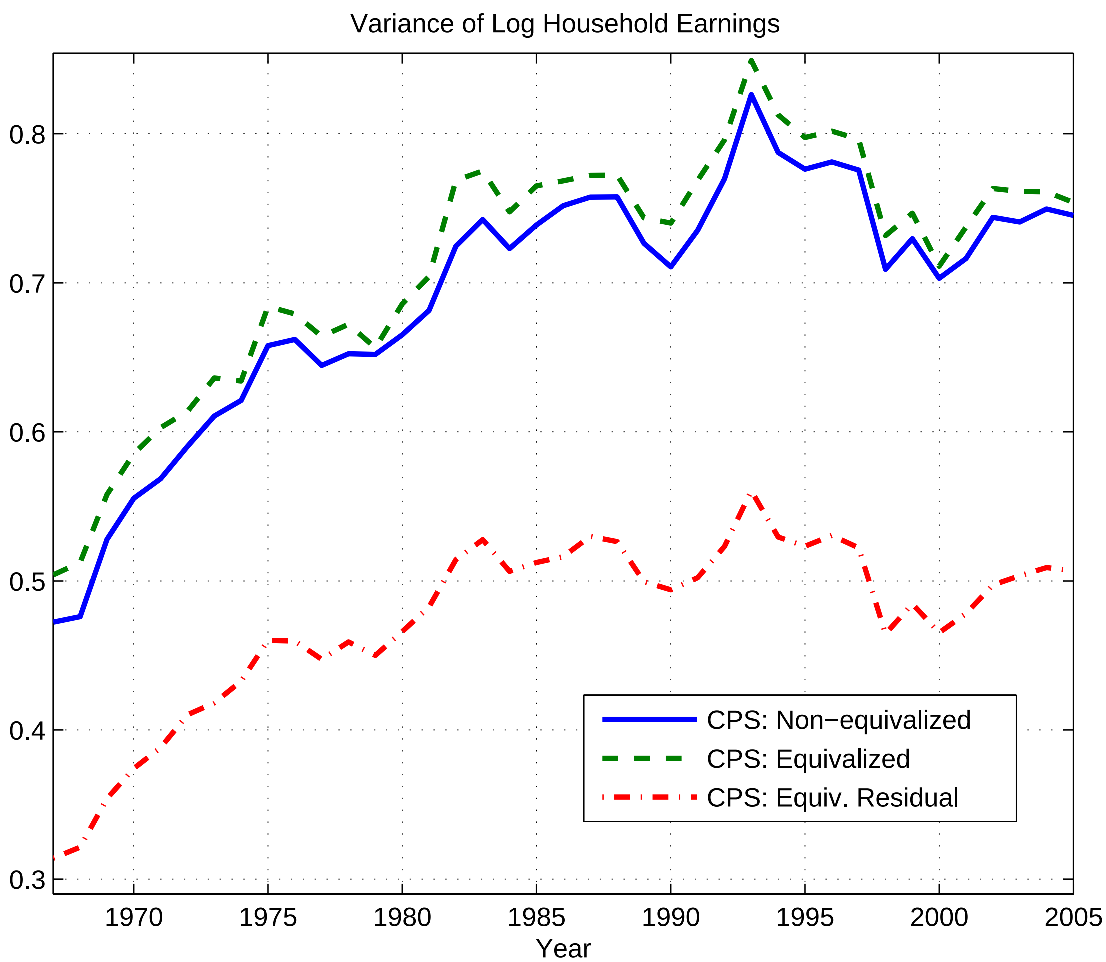

Figure 9: Variance of log household earnings inequality: raw, equivalized and residual

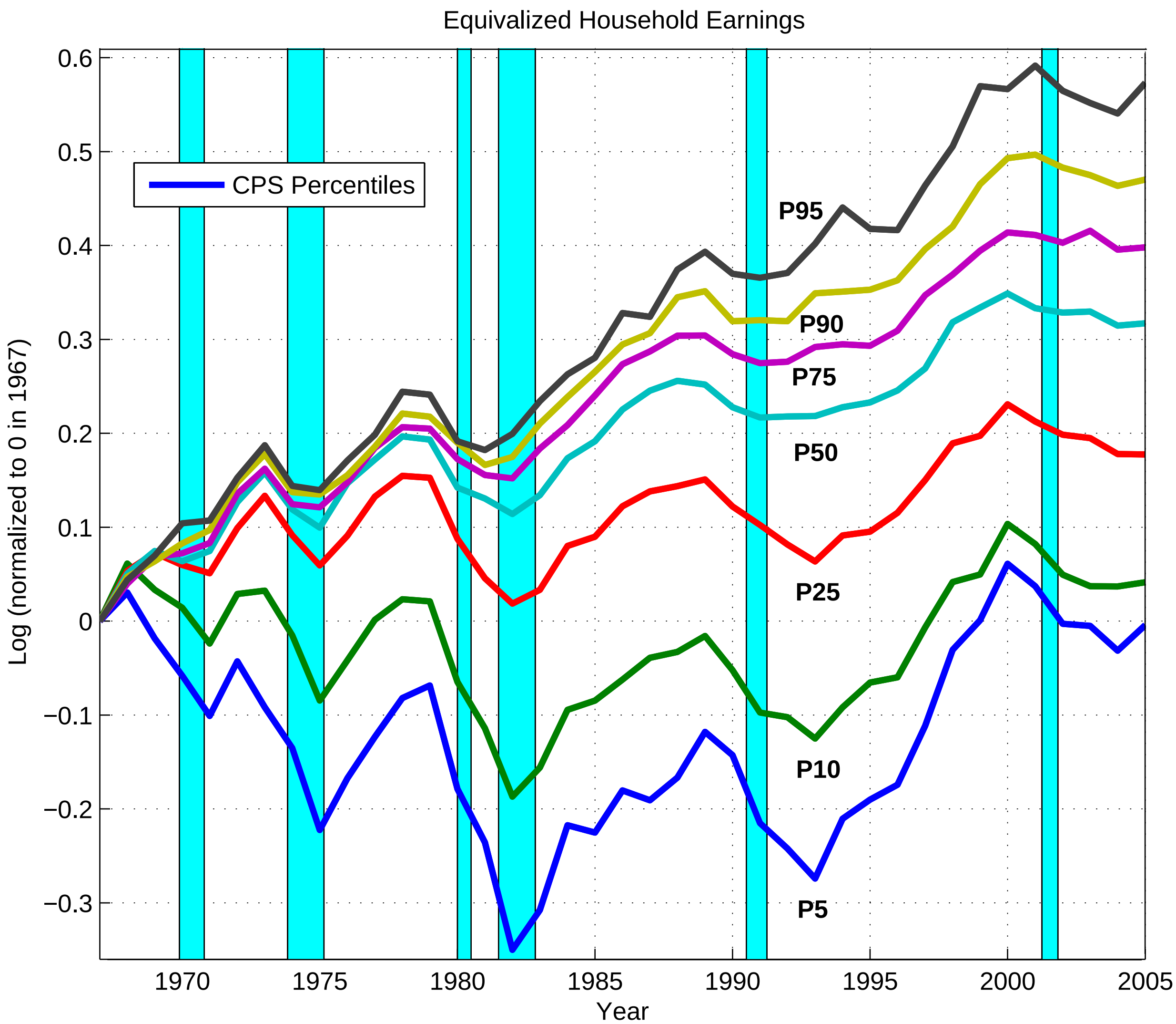

Figure 10: Percentiles of the household earnings distribution (shaded areas are NBER recessions)

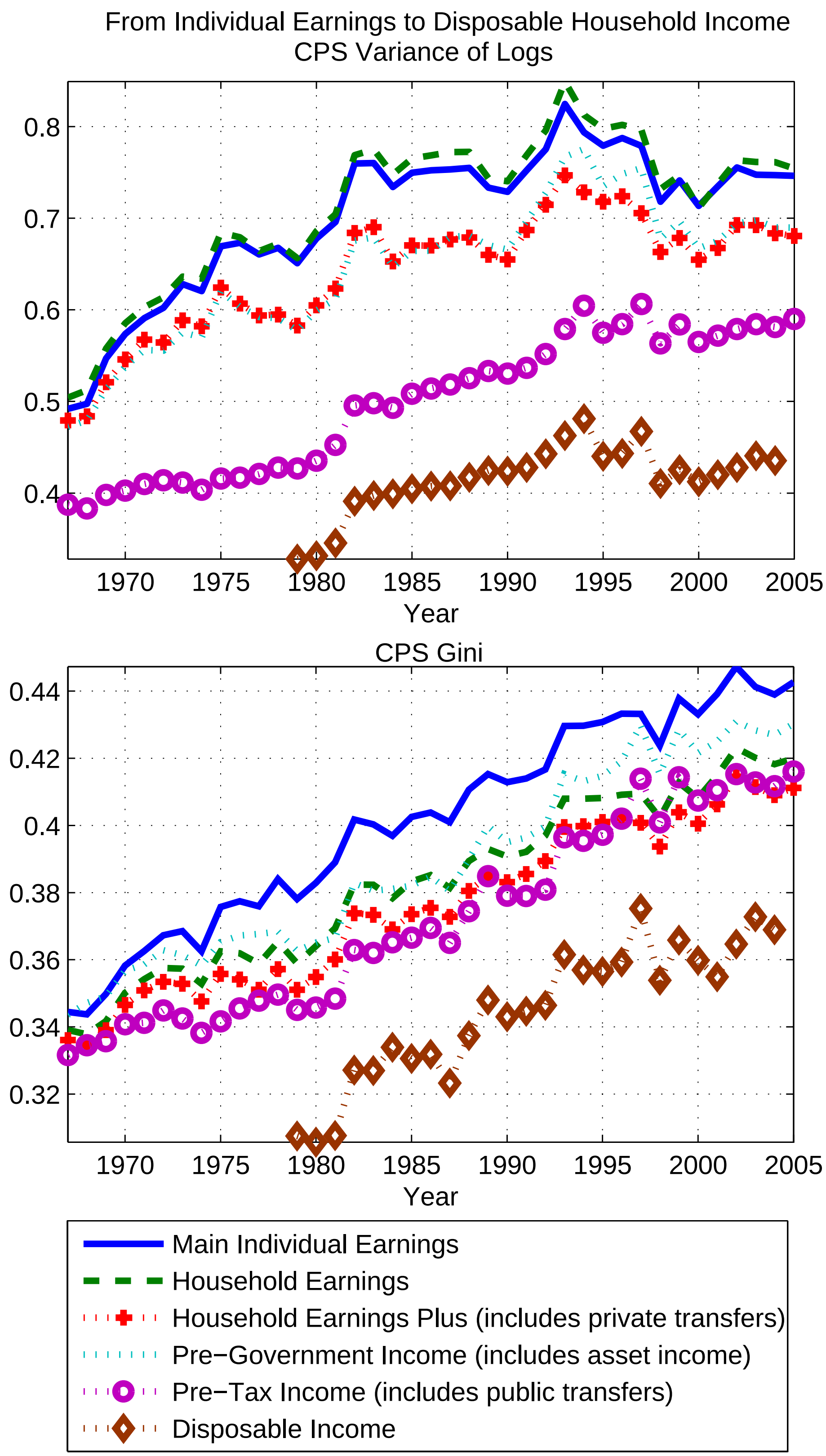

Figure 11: From individual earnings inequality to household disposable income inequality

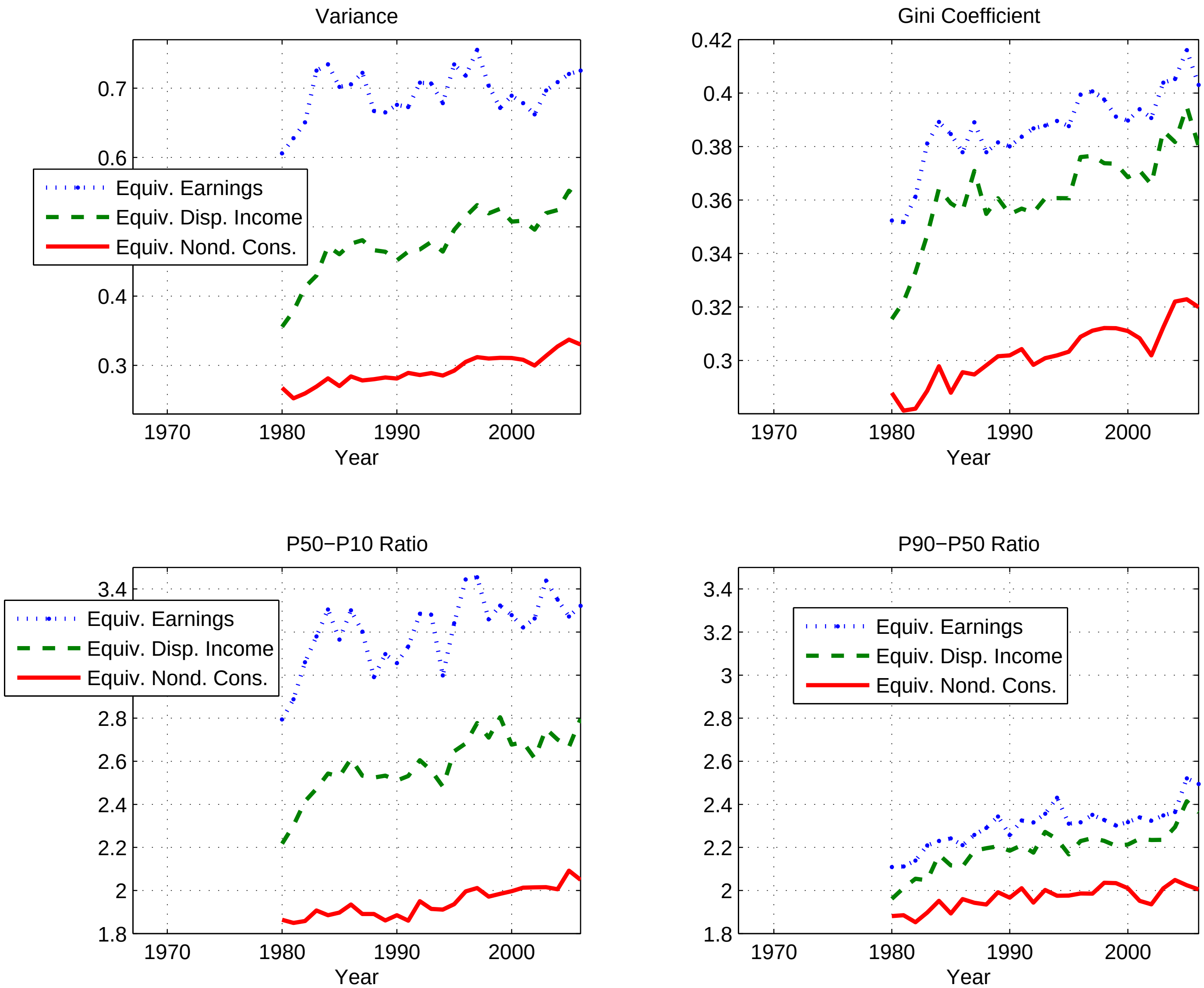

Figure 12: From household earnings inequality to nondurable consumption inequality in CEX.

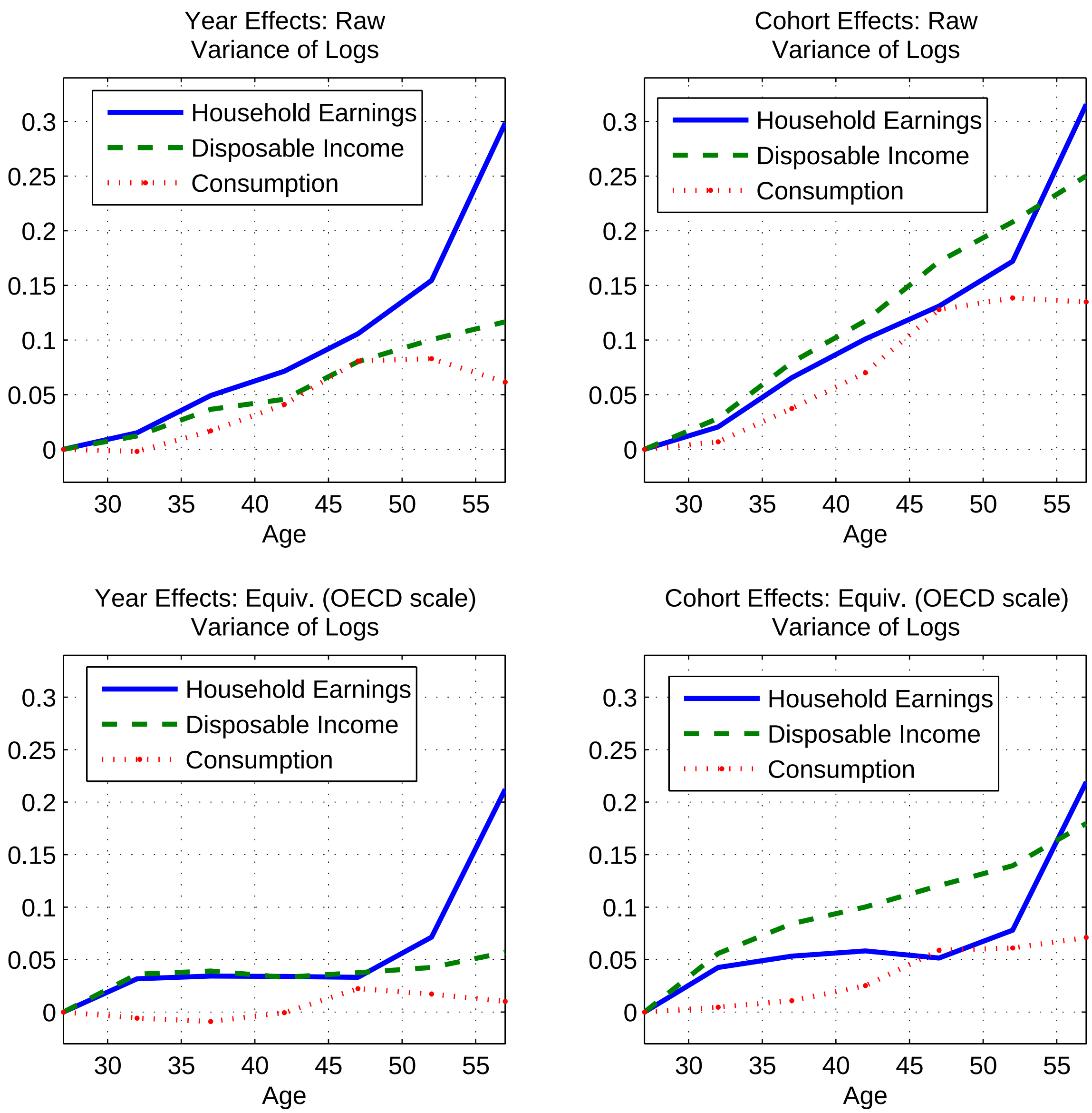

Figure 13: Life-cycle inequality in CEX: controlling for time and cohort effects

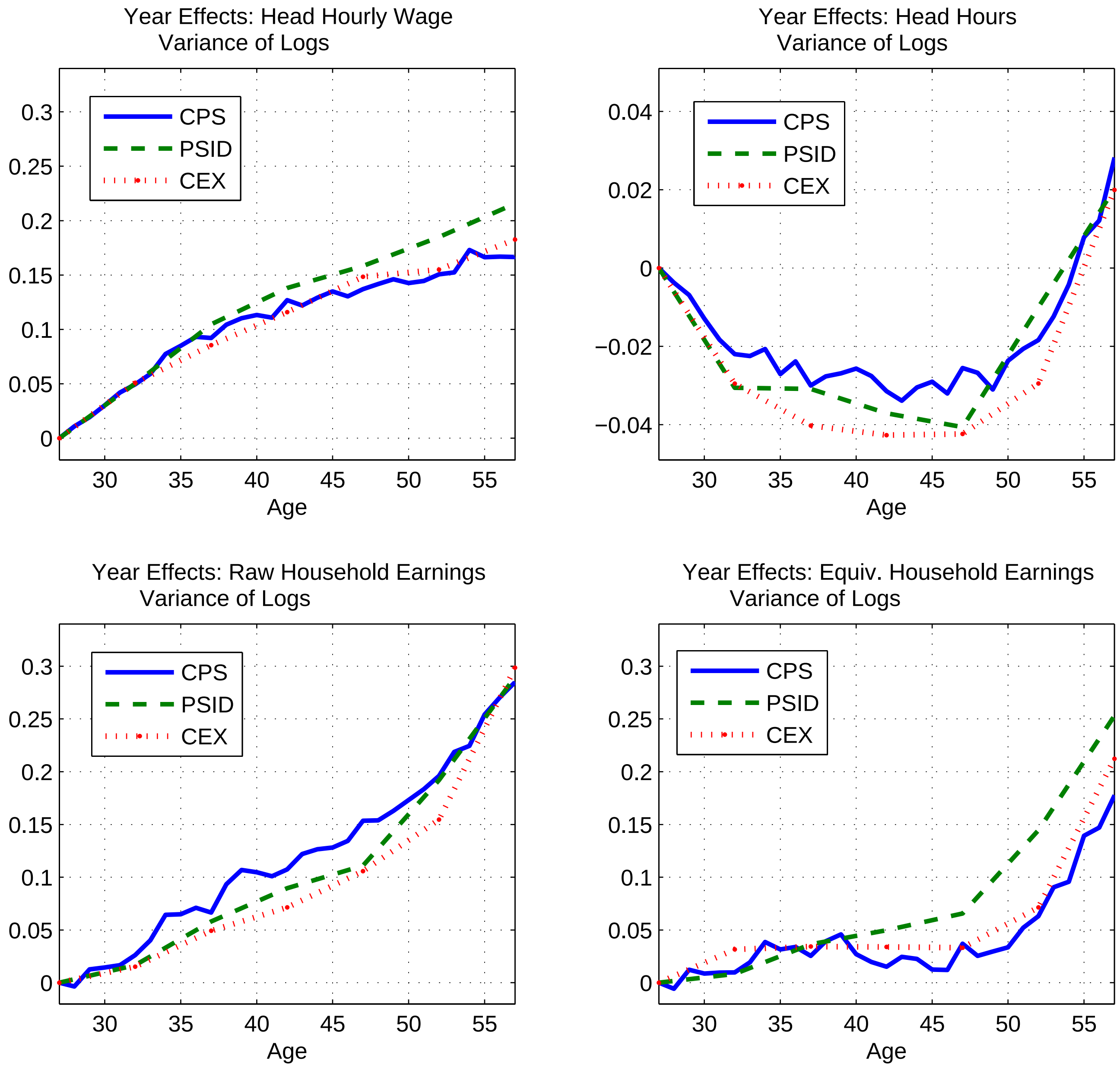

Figure 14: Comparing datasets: inequality over the life-cycle

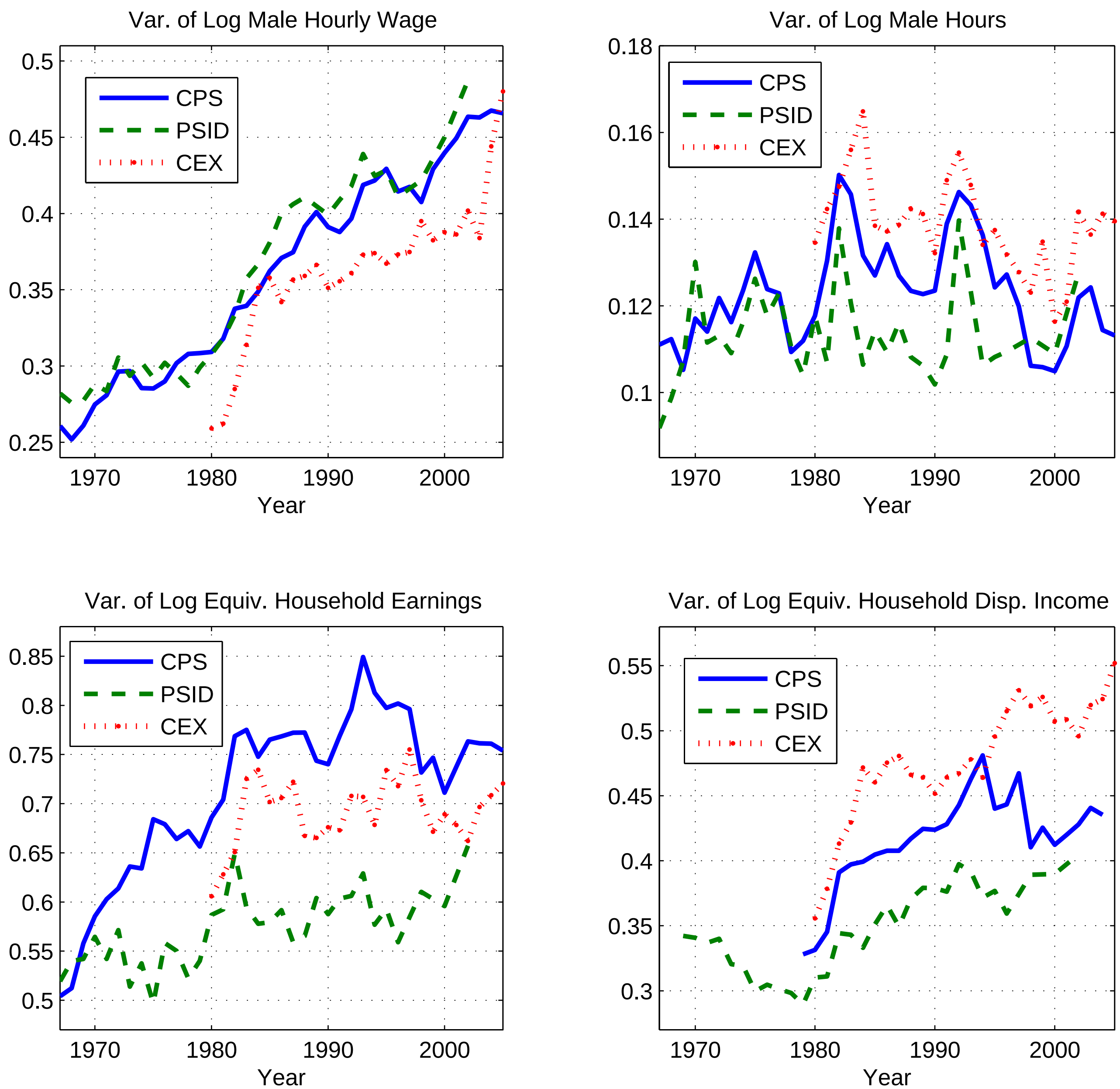

Figure 15: Comparing datasets: variance of logs over time

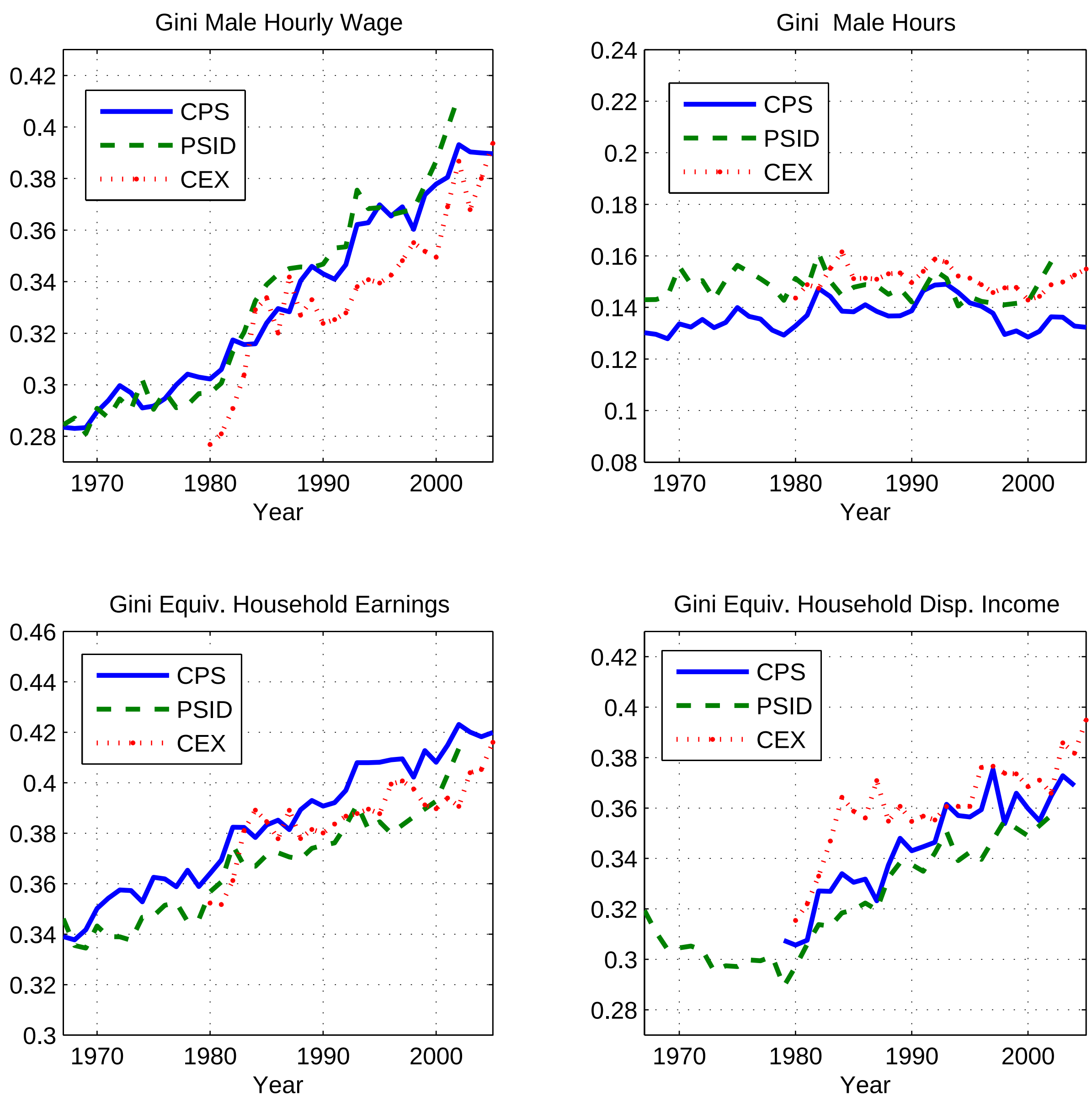

Figure 16: Comparing datasets: Gini coefficient over time

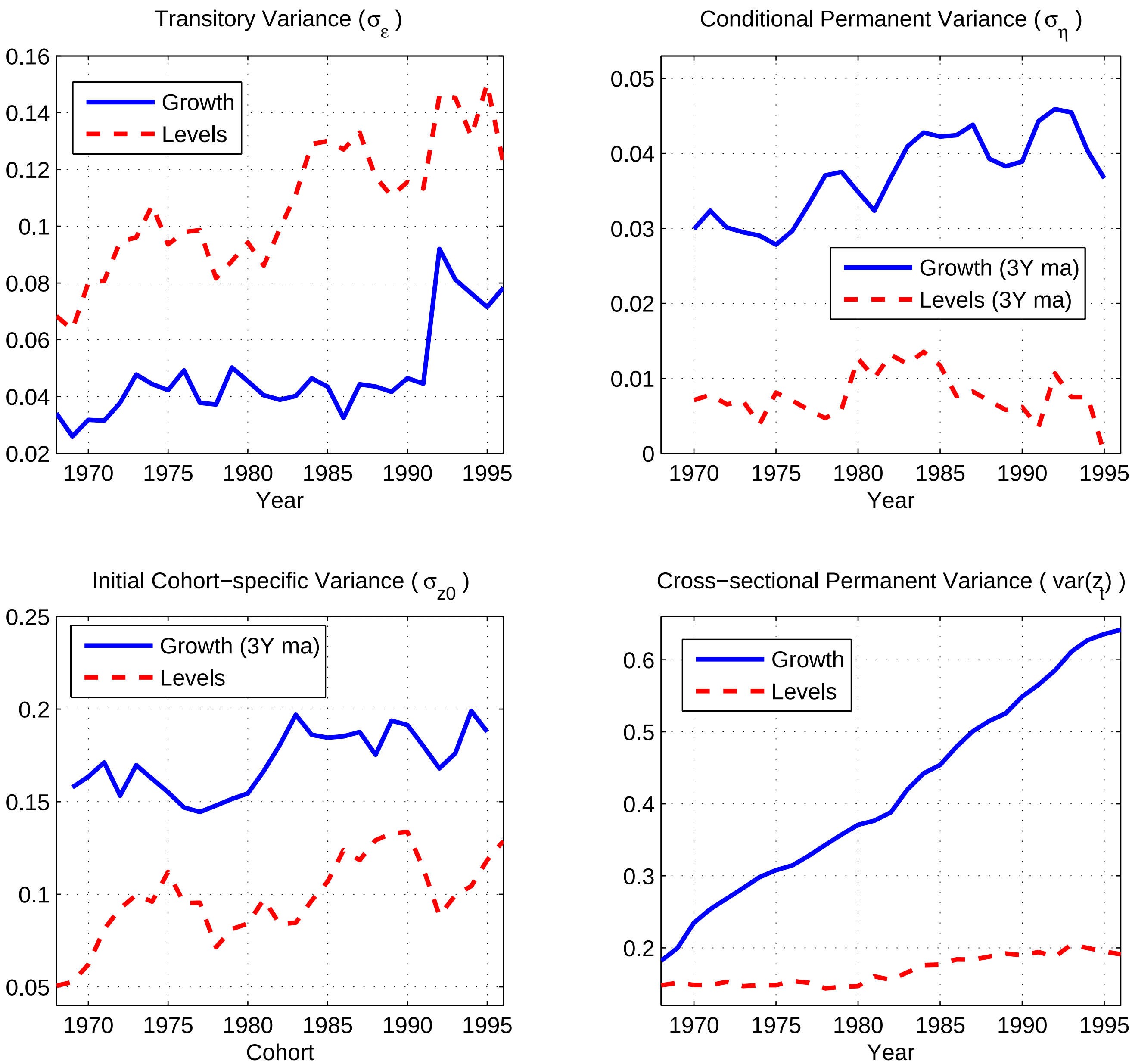

Figure 17: Parameter estimates for the permanent-transitory model

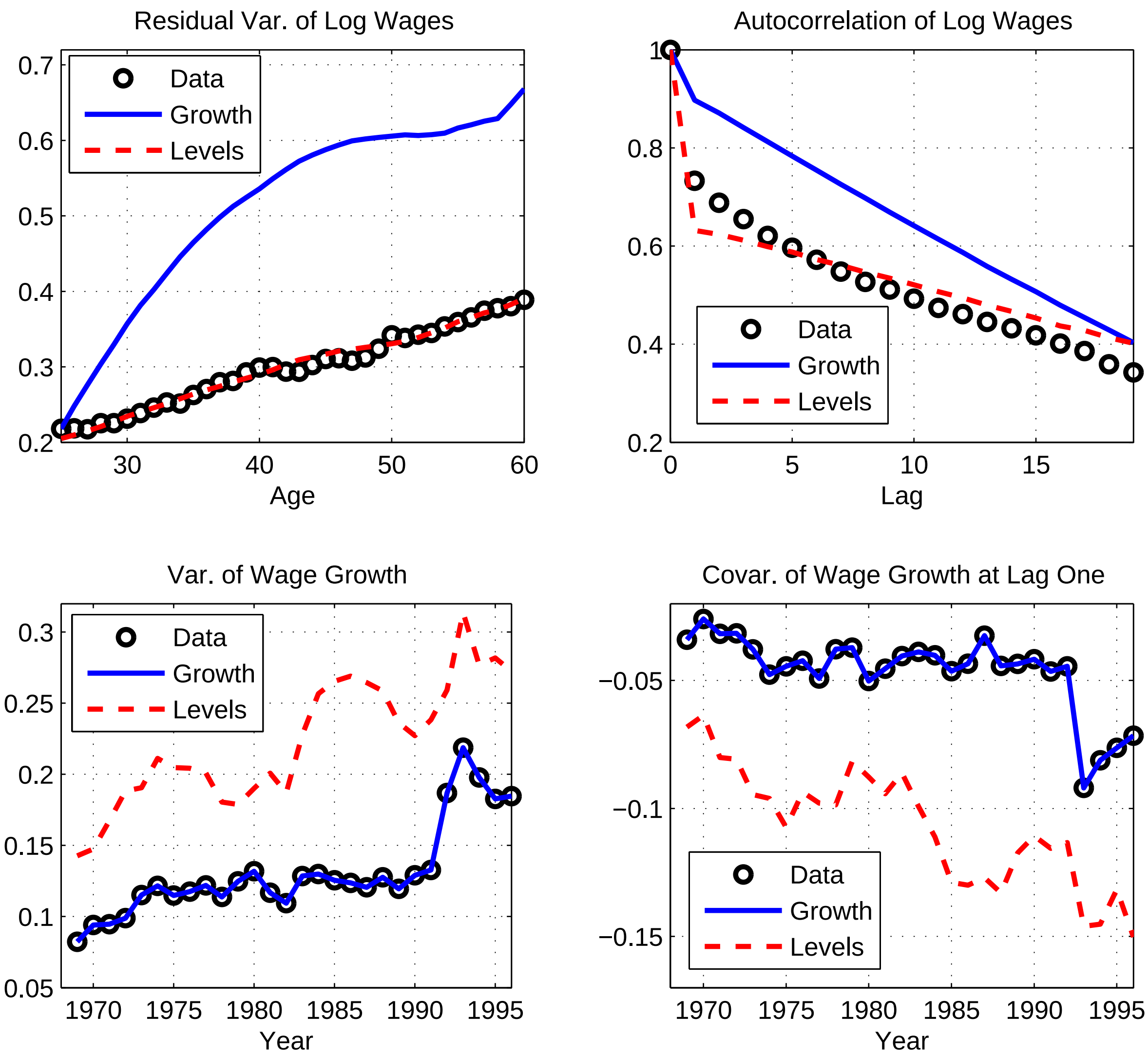

Figure 18: Fit of the permanent-transitory model