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Inequality and dynamics of earnings and disposable income in Denmark 1987–2016

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We document facts about earnings and disposable income inequality and growth in Denmark in the period 1987–2016. During this period, the distribution of log earnings growth exhibits skewness that varies with the business cycle and has strong excess kurtosis. Denmark has a progressive income tax system with a high level of taxes and a relatively generous and heavily subsidized unemployment insurance system. Consequently, the dispersion of log disposable income growth is much smaller than for earnings, and the distribution exhibits very limited skewness and much reduced excess kurtosis. These results emphasize the importance of distinguishing between earnings and disposable income when modeling income dynamics, and they suggest that the Danish welfare state plays an important role in reducing the impact of earnings fluctuations on disposable income.

Keywords. Inequality, income dynamics, earnings, disposable income.

JEL classification. D31, H24, J31.

1. Introduction

This paper documents facts about earnings and disposable income inequality and growth in Denmark during the period 1987–2016.

Denmark is an interesting case for at least three reasons. First, Denmark has well-developed research data infrastructure, making it possible to measure the dynamics of income inequality for the entire population, and not only for earnings but also for disposable income and both at the individual and at the household level. Second, there is a high level of redistribution, implying that there are likely to be important differences in the distribution of the levels and growth rates of pre-tax earnings and disposable income, including transfers. Third, since the beginning of the 1990s, a sequence of policies has reduced the marginal tax rate on earnings from 68 to about 56% today, while at the same time, the generosity of transfers has been reduced in several dimensions, for example, by shortening the period of potential unemployment insurance benefits and by lowering the average replacement rate.

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The paper contains two parts. In part one, a set of facts about the level of earnings inequality and the dynamic properties of earnings is presented. We find that the level of inequality has increased over the period considered, in particular over the last 20 years. The majority experienced a steady increase in the level of earnings over the period, but men belonging to the bottom 10% of the distribution experienced a decline. The dispersion of earnings is most predominant in the bottom half of the distribution where the dispersion is almost double that of the top half. Also, while inequality in the bottom half of the distribution is quite business-cycle dependent and rising during recessions, it is stable in the top half.

The picture for earnings dynamics, that is, log earnings growth rates, looks different. Here, dispersion is similar for the top and the bottom halves of the distribution. The distribution of earnings growth rates exhibits moderate skewness, with positive skewness during booms and negative skewness during recessions, and it exhibits significant excess kurtosis. We do not find large differences in the patterns of income dynamics for men and women. This is likely due to the fact that education levels are similar and the female labor force participation rate was relatively high in Denmark throughout the observation period.

Part two is devoted to describing the development of the distribution of log disposable income and its growth rate. We document that the the level of inequality has increased since around 2005. The properties of disposable income dynamics are quite different from those of earnings. As a consequence of significant and progressive income taxation and relatively generous unemployment insurance (UI) benefits in Denmark, the dispersion of disposable income growth is about half that of earnings. Moreover, the distribution of disposable income growth exhibits practically no skewness and much less excess kurtosis than earnings growth. Finally, dispersion, skewness and excess kurtosis of disposable income growth are remarkably stable over the three decades considered. These results suggest that redistribution through the tax and transfer system is quite effective in ironing out much of the earnings fluctuations faced by individuals.

Our paper contributes to the collection of results presented in this volume by documenting trends in earnings dynamics in Denmark. One set of results worth highlighting shows that the distribution of log earnings growth exhibits procyclical skewness, that is, it tends to be positive during booms and negative during recessions. Procyclical skewness of the log earnings growth distribution has previously been documented for Denmark (Harmenberg (2021)) as well as for several other countries, including the US (Pruitt and Turner (2020), Guvenen, Ozkan, and Song (2014)), Norway (Halvorsen et al. (2019)), and Sweden, Germany, and France (Busch, Domeij, Guvenen, and Madera (2022)). Another interesting finding is that the properties of earnings growth are very similar for men and women in Denmark. Related to this, the results for household earnings are very similar to those of individual earnings, indicating that there is little insurance provided within the household by way of an added-worker effect.

A second contribution is to show how different the properties of earnings and disposable income are for Denmark. We show that skewness and excess kurtosis are much less pronounced for disposable income growth than for earnings growth and, of course, that the variance of disposable income is much smaller due to the substantial redistribution through the tax and transfer systems. These findings add to the evidence by De Nardi, Fella, Knoef, Paz-Pardo, and Van Ooijen (2021) who study the Netherlands, Blundell, Graber, and Mogstad (2015) and Halvorsen et al. (2019), both studying Norway, and Busch et al. (2022) studying Sweden. They show that the tax and transfer income system is important in reducing earnings fluctuations that workers face in these countries and jointly point toward the importance of taking into account the institutional structure when characterizing income growth.

The next section of the paper describes the data and institutional features that are relevant to keep in mind. Section 3 presents the part that is in common with the other papers in this volume. Section 4 compares the properties of earnings and disposable income. The final section sums up and concludes. The Online Appendix may be found in the Supplementary Material (Leth Petersen and Sæverud (2022)).

2. Data and institutions

The results presented in this paper are based on merged administrative data covering the entire Danish population for the period 1987 to 2016. The various administrative registers are collected by Statistics Denmark from relevant public authorities and made available to researchers. The core data set used in this paper is compiled by the Danish Tax Agency, which collects information about earnings for all employees directly from all employers in Denmark. Earnings include the value of fringe-benefits, severance payments, and the value of stock options, but they do not include contributions to employer pension accounts, since these are tax deductible and are subtracted at the payroll level. As taxes are calculated based on gross income, including transfer income, we measure earnings before taxes. The tax authorities also collect information about total income, including transfer income, and annual tax payments through the annual tax return, where most entries are also third-party reported. None of the income measures are top coded. Tax evasion is known to be very limited and the data to be of a high quality (Jacobsen Kleven, Knudsen, Thustrup Kreiner, Pedersen, and Saez (2011)). Moreover, there is no attrition other than due to migration and death.

Data on various types of income are linked to other administrative data sets through a personal ID number, which is applied universally by the public sector. We exploit this to link the income-tax data to, among other things, the population register, which allows us to connect individuals to partners.

All economic variables are deflated using the consumer price index with 2018 as the base year. We impose a few restrictions on the gross data set. First, we only include individuals who are aged 25–55 and who have positive earnings. Next, we include only individuals who have both earnings and disposable income amounting to at least 28,500 DKK annually (2018 prices). In terms of earnings, this roughly compares to the level for a part-time job held for one quarter.[1] For the results on inequality in levels, we use raw

[1] In robustness checks, we tried lower limits and imposing limits on only earnings or only disposable income. We also tried winsorizing values below the limits, and these exercises did not change the results reported in the paper in any important way.

log measures, and for the results on inequality in growth rates we use the residuals from an OLS regression of the log of earnings or disposable income on age dummies, run separately by year and gender.[2]

Throughout the paper, we use three different samples:

- Cross-sectional (CS) includes all observations
- Longitudinal (LS) includes only individuals with observations in $t+1$ and $t+5$ to be able to capture within-individual changes over time
- Heterogeneity (H) includes only those with observations in $t+1$ and $t+5$ and with observations in t, $t-1$, and $t-2$. This lets us group individuals by permanent income, proxied by a 3-year average

Together with the other Scandinavian countries, Denmark is known for its well-developed welfare state that provides free health and old-age care, free child care, free education, and generous UI benefits. The female labor force participation rate is high, at about 80%. About 80% of Danish workers are members of a UI fund. UI fund membership costs between 450–500 DKK per month (1USD$\approx$ 6.5 DKK, 2018 level). UI benefits replace up to 90% of the income in the previous job and are capped such that you can at most receive 18,633 DKK per month (2018 level). This roughly compares to the level of income earned in a full-time job for an unskilled worker paid the minimum wage rate.[3] Through the period considered in the paper, the potential duration of UI benefits has been reduced in several steps: In 1993, the potential duration was limited from 8 to 7 years, in 1996 to 5 years, in 1999 to 4 years, and, finally, in 2010 it was reduced to 2 years. Moreover, UI benefits are indexed by the consumer price index and not by a wage index. Figure 1 shows that the replacement rate of UI benefits compared to mean wages has shrunk from about 60% to close to 45% over the period, since wages have grown more than consumer prices.

The flip-side of the welfare state is, of course, a relatively high level of taxation. However, over the observation period, a number of tax reforms that lowered the marginal tax rate at all levels of income were implemented. For example, for top taxpayers, the marginal tax rate was 68% in 1987 and 56% in 2010; see Jacobsen Kleven and Schultz (2014) and Thustrup Kreiner, Leth-Petersen, and Ebbesen Skov (2016). In sum, across the period considered, a sequence of UI-benefits and tax reforms have reduced the value and duration of UI benefits and lowered the marginal tax rate on earnings. These changes would, all else equal, be expected to have contributed to increasing the cross-sectional dispersion of disposable income over the period 1987–2016.

Table 1 presents selected summary statistics for earnings for the sample in the years 1995 and 2015. All monetary values are reported in US dollars, converted from Danish

[2]All growth rates are calculated as forward looking, that is, the difference between $t+1$ and t.

[3]For people who are not members of a UI fund, it is possible to qualify for cash benefits. Cash benefits are paid by the municipality, and at 11.554 DKK per month, provide a significantly lower level of payments. Rates are lower for people aged less than 30, but are higher for parents. Cash benefits are means tested at a very low threshold (10,000 DKK) which, in practice, only allows people to hold a minimal transaction balance.

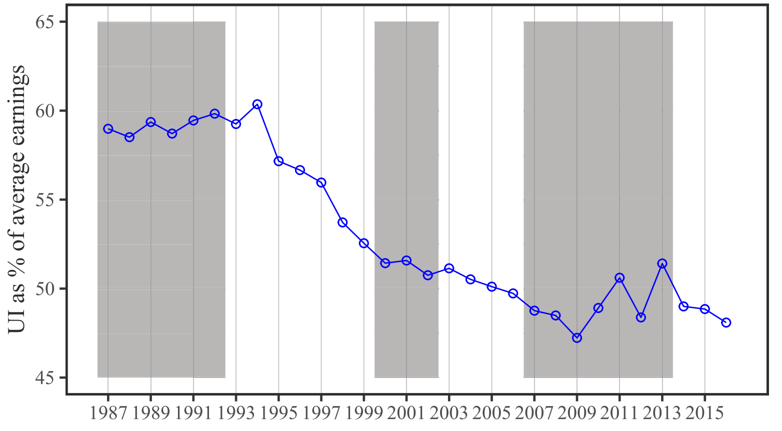

FIGURE 1. Unemployment insurance benefits relative to average earnings. *Notes*: The figure shows the maximum UI benefits relative to the average earnings level among people with a job. The shaded areas indicate recessionary periods where the GDP growth rate is below 2%.

Kroner (2018 prices) using yearly exchange rates. The sample that we analyze includes 1.8 to 1.9 million observations per year. The average level of income for women is about 25–30% lower than for men, and the gap is shrinking over time. Hence, men's average earnings have grown about 17% over the two decades from 1995–2015, while they have grown about 27% for women over the same period. Perhaps the most radical change over the observation period concerns education: Going from 1995 to 2015, there was a significant lift in the overall level of education.

In the bottom panel, selected percentiles of the earnings distribution are tabulated for 1995 and 2015.[4] This shows an interesting pattern where the growth has largely taken place in the upper part of the earnings distribution. For example, earnings at the 10th

TABLE 1. Descriptive statistics for different samples.

Year	Obs.	Women	Mean Earnings		Age Shares %			Education Shares %				
	(Mill)	% Share	Men	Women	[25, 35]	[36, 45]	[46, 55]	$< HS$	HS	VOC	CD	$> CD$
1995	1.85	47.6	58,122	41,698	37.5	32.0	30.5	23.1	6.7	38.9	23.3	7.9
2015	1.82	48.6	68,127	52,877	31.5	33.3	35.2	16.5	12.7	29.1	27.8	13.9

Year	p1	p5	p10	p25	p50	p75	p90	p95	p99	p99.9
1995	5908	11,243	18,761	35,894	48,675	61,034	78,219	93,287	136,816	248,466
2015	5926	11,509	19,519	41,128	56,310	72,678	95,979	118,282	194,773	471,735

Note: The table shows selected summary statistics for the sample for 1995 and 2015. All monetary values are summarized in US dollars by converting 2018 Danish Kroner values to US dollars using yearly exchange rates. *HS*: High School, *VOC*: Vocational Education, *CD*: College Degree.

[4]For data protection reasons, all quantile-based measures presented in the paper are calculated as a mean of five observations around the quantile. Due to the large sample size, this practically leaves the results unaffected.

percentile are practically unchanged, while median earnings have grown 16%, and earnings at the 90th percentile have grown 23%. In the next section, we present numbers describing the distribution of earnings for the entire period 1987–2016.

3. Trends in the inequality and dynamics of earnings

This section presents a set of key facts about the distribution of the level and the growth of log earnings. We start out by presenting the percentiles of the level of log earnings by year. After that, we turn to consider income inequality, both in the cross-section and by cohort over the life cycle. We then turn to the dynamics of earnings and consider the dispersion, skewness, and excess kurtosis of the distribution of 1-year changes in residualized log earnings. Finally, we consider income mobility. All of these statistics are reported separately for men and women.

Figure 2 presents selected percentiles of the log earnings distribution for men and women. In all cases, the percentiles are indexed by their level in 1987. The inequality in levels has increased over the period considered as evidenced by the fanning out of the quantiles of the distribution over time in panels (a) and (b). The majority experienced a steady increase in the level of earnings over the period. One exception is men belonging to the bottom 10% of the distribution, who experienced a decline. Also, fluctuations at the 10th percentile are more strongly synchronized with the business cycle than the other percentiles, suggesting that this group is more loosely attached to the labor market. In panels (c) and (d), we show selected percentiles at the top of the distribution. The absolute top of the earnings distribution, that is, the top 0.01%, appears to have taken off over the past 20 years.

Overall, Figure 2 shows that inequality in the *level* of income has increased and especially the very top and the bottom are drifting further apart. The figures are remarkably similar for men and women.[5]

Figure 3 measures the dispersion directly. Panels (a) and (b) present two measures of dispersion, $2.56\times\sigma$ and the distance between the 90th and the 10th percentile, p90–p10, in the distribution. Throughout the rest of the paper, we only consider the robust dispersion measure, as it is less sensitive to outliers. Both measures suggest a tendency toward an increase in the dispersion of the overall earnings distribution, particularly since the financial crisis, but the dispersion tends to increase during recessionary periods. Again, the pattern is relatively similar between men and women. Panels (c) and (d) plot the time series of the difference between the 90th percentile and the median, p90–p50, and the difference between the median and the 10th percentile, p50–p10. For both men and women, the evidence suggests that the dispersion is highest at the bottom part of the distribution of earnings and also that it is more business cycle dependent. In fact, for the top part of the distribution, dispersion is quite stable, albeit with a weak tendency to increase over the period.

Figure 4 considers the dispersion of initial earnings, which in this context is defined as earnings at age 25. Again, the panels show the time series of the difference between

[5] In Appendix A, we present figures for the whole sample of men and women combined. These figures look qualitatively similar to the gender specific versions.

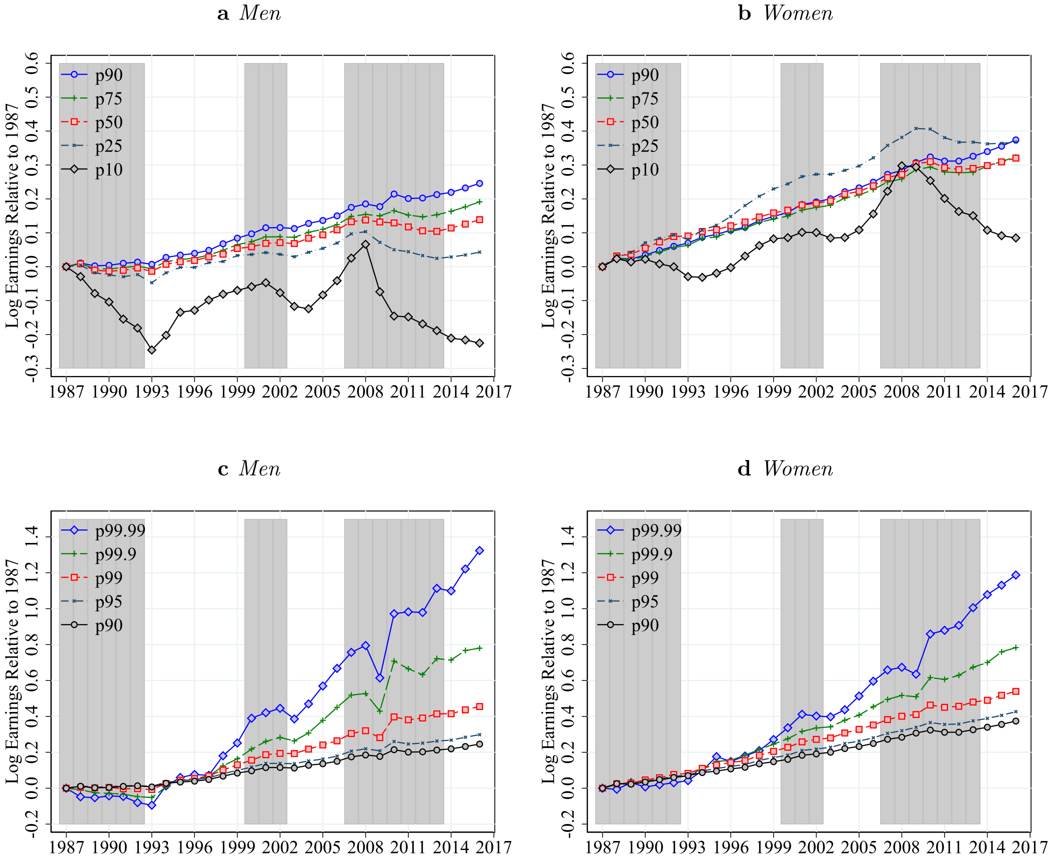

FIGURE 2. Change of percentiles of the log real earnings distribution. *Notes*: The figure plots raw log earnings for selected percentiles where all percentiles are normalized to 0 in the first available year. CS sample. The figure plots the following variables against time: (a) Men: p10, p25, p50, p75, p90 (b) Women: p10, p25, p50, p75, p90, (c) Men: p90, p95, p99, p99.9, p99.99, (d) Women: p90, p95, p99, p99.9, p99.99. The shaded areas indicate recessionary periods where the annual GDP growth rate is below 2%.

the 90th percentile and the median, p90–p50, and the difference between the median and the 10th percentile, p50–p10, of the initial earnings level. For this statistic, the dispersion is also bigger at the bottom of the distribution, but there is a tendency for dispersion at the top and at the bottom of the earnings distribution to converge. Compared to the dispersion of the overall distribution shown in Figure 3, the dispersion of the initial earnings distribution seems to be less business cycle dependent. This could suggest that business cycle variation in the dispersion is not caused by business cycle variation in entry wages. Again, the pattern is quite similar for men and women.

So far we have only considered cross-sectional measures of the earnings distribution. Figure 5 plots the life-cycle paths for four selected birth cohorts. The solid lines track the within-cohort earnings dispersion, measured by the p90–p10 distance, across time, and the dashed lines track the dispersion for people at different ages, 25, 30, 35,

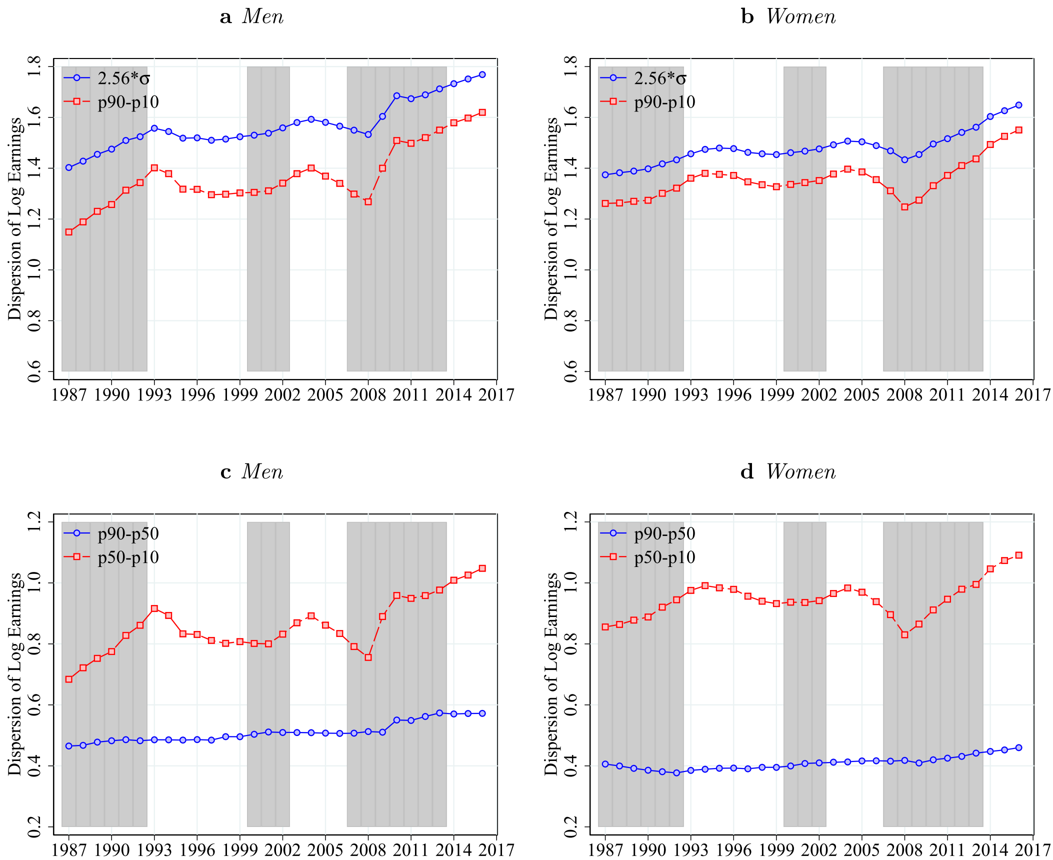

FIGURE 3. Earnings inequality. *Notes*: The figure plots dispersion of raw log earnings. CS sample. The following variables are plotted against time: (a) Men: p90–p10 and 2.56*σ of log earnings, where σ is the standard deviation. (b) Women: p90–p10 and 2.56*σ of log earnings (c) Men: p90–p50 and p50–p10, (d) Women: p90–p50 and p50–p10. The shaded areas indicate recessionary periods where the annual GDP growth rate is below 2%. 2.56*σ corresponds to the p90–p10 differential for a Gaussian distribution.

and 40. The pattern is striking. The dispersion is relatively constant within ages across time (as evidenced by the roughly constant horizontal dashed lines), but it declines drastically with age, as indicated by the downward sloping cohort lines.

The pattern, where the difference between the 90th and 10th percentiles, p90–p10, is decreasing over the life cycle, is similar to Norway (Halvorsen, Ozkan, and Salgado (2022)) and Sweden (Friedrich, Laun, and Meghir (2022), and to some degree, France (Kramarz, Nimier-David, and Delemotte (2022)), Brazil (Engbom, Gonzaga, Moser, and Olivieri (2022)), Argentina (Blanco, Diaz de Astarloa, Drenik, Moser, and Trupkin (2022)), and Germany (Drechsel-Grau, Peichl, Schmid, Schmieder, Walz, and Wolter (2022)), but it appears not to be the typical pattern in Canada (Bowlus, Gouin-Bonenfant, Liu, Lochner, and Park (2022)), the UK (Bell, Bloom, and Blundell (2022)), Italy (Hoffmann, Malacrino, and Pistaferri (2022)), Spain (Arellano, Bonhomme, De Vera, Hospido, and

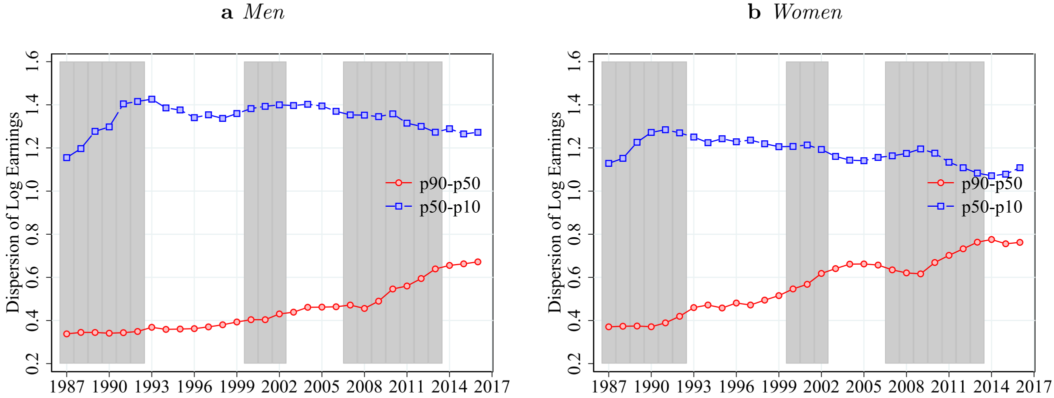

FIGURE 4. Income inequality at age 25. *Notes*: The figure plots dispersion of raw log earnings. CS sample at age 25. The following variables are plotted against time: (a) Men: p90–p50 and p50–p10, (b) Women: p90–p50 and p50–p10. The shaded areas indicate recessionary periods where the annual GDP growth rate is below 2%.

Wei (2022)), and Mexico (Puggioni, Calderón, Cebreros Zurita, Fernández Bujanda, Gonzalez, and Jaume (2022)).

In Figure 6, we decompose this result into p50–p10 and p90–p50. Consistent with the pattern shown in Figure 3, most of the dispersion comes from the bottom part of the distribution and the figure clearly shows that the downward trend in life-cycle inequality with age is driven by p50–p10. Life-cycle dispersion at the upper end of the distribution is relatively modest and does not change much over the life cycle.

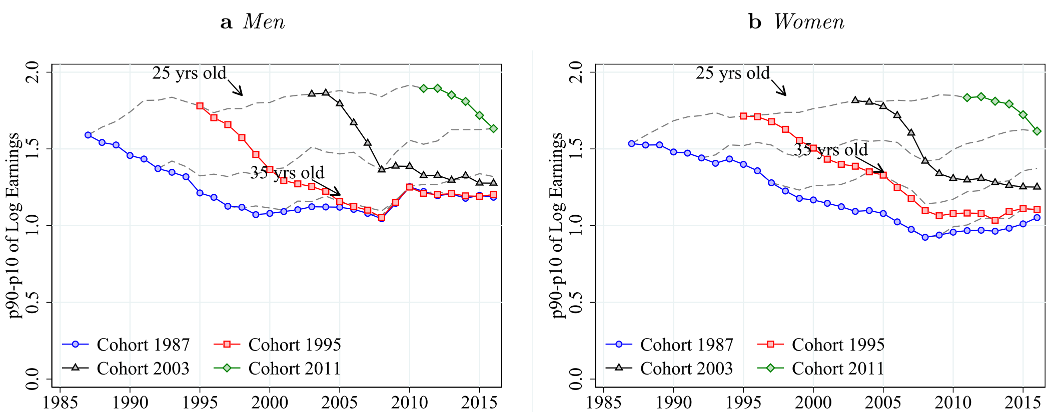

FIGURE 5. Life-cycle inequality over cohorts. *Notes*: The figure plots life-cycle profiles of dispersion of raw log earnings. CS sample. The following variables are plotted against time: (a) Men: p90–p10 over the life cycle for four selected cohorts (indexed by age 25), (b) Women: p90–p10 over the life cycle for four selected cohorts (indexed by age 25).

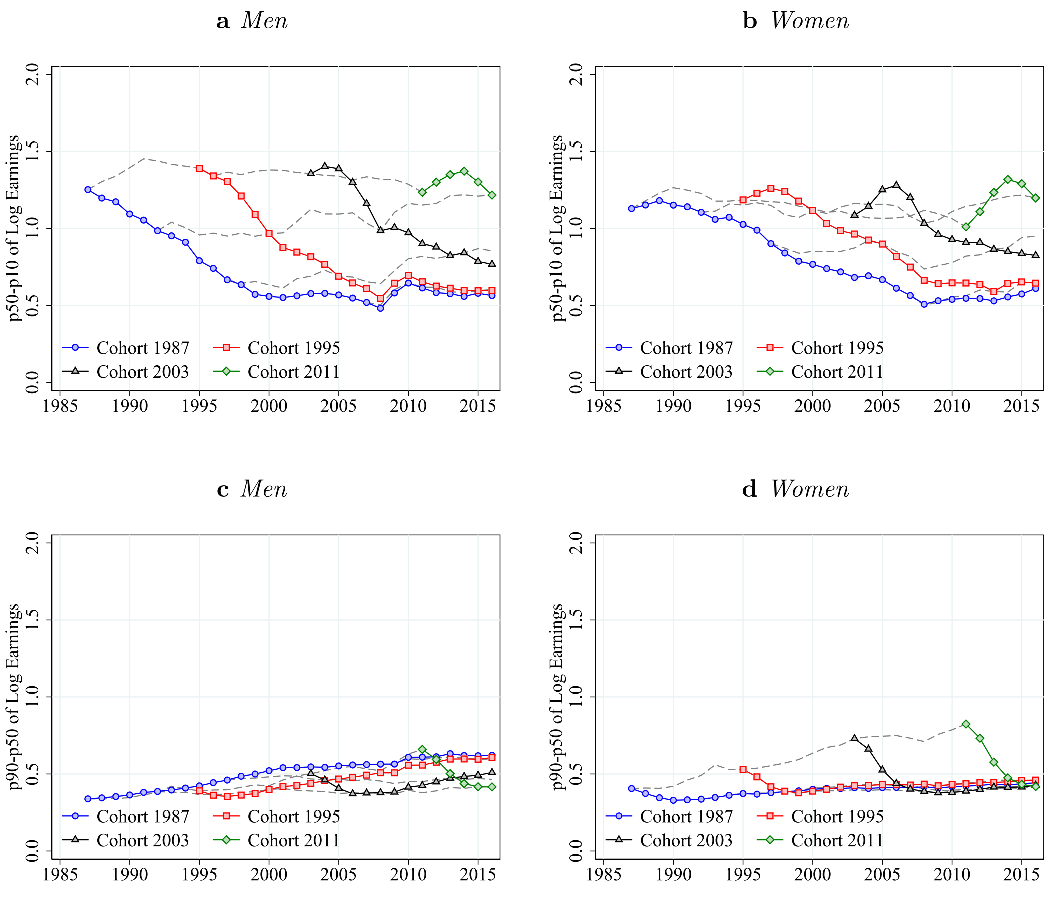

FIGURE 6. Life-cycle inequality over cohorts for above and below median income. *Notes*: The figure plots life-cycle profiles of dispersion of raw log earnings. CS sample. The following variables are plotted against time over the life cycle for four selected cohorts (indexed by age 25): (a) Men: p50–p10, (b) Women: p50–p10, (c) Men: p90–p50, (d) Women: p90–p50.

3.1 *Growth rate dynamics for earnings*

We now turn to considering the dispersion and higher moments of the distribution of residualized log earnings growth rates. ε_{it} is the individual and time specific residual from an OLS regression of the log earnings on age dummies, run separately by year and gender. The 1-year growth rate is defined as $g^1_{it} = \Delta\varepsilon_{it} = \varepsilon_{it+1} - \varepsilon_{it}$.

Figure 7 displays the time series of the dispersion, p90–p10, as well as the difference between the 90th percentile and the median, p90–p50, and the difference between the median and the 10th percentile, p50–p10, for the distribution of residual log earnings growth rates, g^1_{it}. By considering the dispersion of the distribution of residual log earnings growth rates, we are now narrowing in on the individual level dynamics. Figure 7 shows that the top and bottom dispersion is quite similar and that this is the case for both men and women. There is a weak tendency that the dispersion of the distribution of residual log earnings growth rates is slightly higher for women than for men, but over-

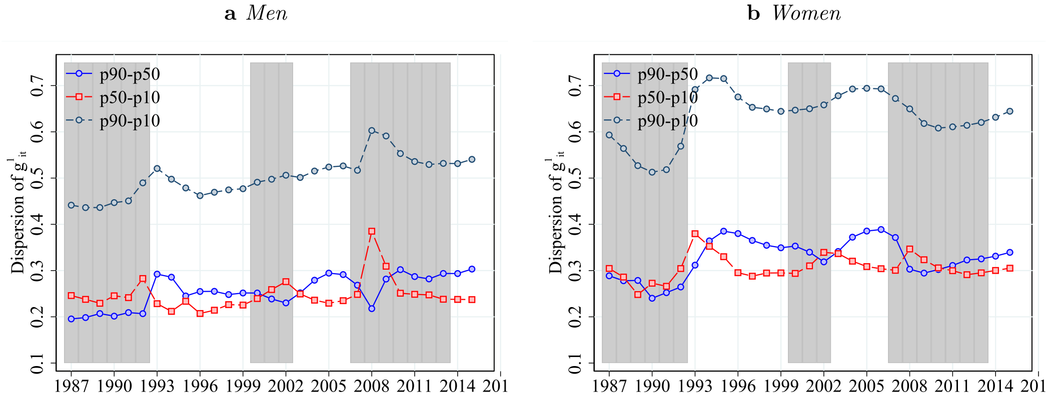

Figure 7. Dispersion of the distribution of 1-year residual log earnings growth rates. Notes: Dispersion of 1-year residual log earnings growth rate, $g_{it}^1 = \varepsilon_{it+1} - \varepsilon_{it}$. LS sample. The figure plots the following variables against time: p90–p50 (solid), p50–p10 (long dash), and p90–p10 (short dash) for men in panel a, and for women in panel b. The shaded areas indicate recessionary periods with GDP growth below 2%.

all, the gender differences are small. There are indications that dispersion in the bottom part of the distribution of residual log earnings growth rates moves procyclically, while dispersion in the top part of the distribution moves countercyclically, but this pattern is not strong. Perhaps most importantly, the level dispersion of the distribution of residual log earnings growth rates appears to be approximately constant when considered over the entire observation period, indicating that the overall level of volatility has not changed.

Figure 8 plots skewness, panel (a), and excess kurtosis, panel (b), for the distribution of residual log earnings growth rates. Throughout the paper, we use robust percentile measures for the 3rd and 4th moments, which are less sensitive to outliers than standardized moments. For skewness, we use Kelley's skewness defined as

$$\frac{(\text{p90–p50}) - (\text{p50–p10})}{\text{p90–p10}}.$$

For kurtosis, we use excess Crow–Siddiqui kurtosis defined as

$$\frac{\text{p97.5–p2.5}}{\text{p75–p25}} - 2.91.$$

Skewness summarizes the extent and direction of asymmetry of the distribution. A positive value means that the distribution exhibits right skewness, such that the mean exceeds the median, and vice versa for a negative value. Kurtosis describes both the peakedness and the heaviness of the tails in a distribution, and it can be interpreted as how likely it is to experience an extreme income change. Excess kurtosis relates the kurtosis of a distribution to the kurtosis of a normal distribution.

According to panel (a) in Figure 8, the overall level of skewness of the distribution of residual log earnings growth rates is relatively small, but it appears to be business cycle

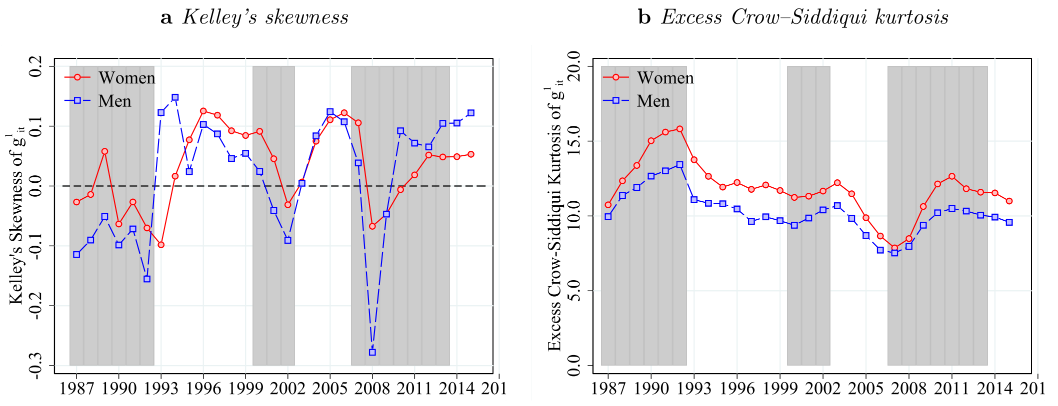

FIGURE 8. Skewness and kurtosis of the distribution of 1-year residual log earnings growth rates. *Notes*: Skewness and kurtosis of the distribution of 1-year residual log earnings growth rates, $g_{it}^1 = \varepsilon_{it+1} - \varepsilon_{it}$. LS sample. The figure plots the following variables against time: (a) Men and Women: Kelley's skewness calculated as $\frac{(\text{p90–p50})-(\text{p50–p10})}{\text{p90–p10}}$, (b) Men and Women: Excess Crow–Siddiqui kurtosis calculated as $\frac{\text{p97.5–p2.5}}{\text{p75–p25}} - 2.91$ where the first term is the Crow–Siddiqui measure of kurtosis and 2.91, corresponds to the value of this measure for a normal distribution. The shaded areas indicate recessionary periods with GDP growth below 2%.

dependent such that right skewness is associated with booms, that is, periods where the annual GDP growth rate is bigger than 2%, and left skewness with recessions, that is, periods where the annual GDP growth rate is less than 2%. The financial crisis in 2008 shows up as an extreme event for men. The recession following the financial crisis shows some right skewness in the years 2010–2014 where the GDP growth rate was positive but smaller than 2%. Note, that Kelley's skewness relates the three different dispersion measures (p90–p10, p90–p50, p50–p10) shown in Figure 7 by calculating the difference between top and bottom dispersion, normalized by total dispersion. As can be seen in Figure 7, top dispersion tends to be more procyclical and bottom dispersion more countercyclical, which is consistent with the fluctuations in Kelley's skewness seen in panel (a) in Figure 8.

We have also investigated other definitions of Kelley's skewness that take more of the income distribution into account by spanning p5 to p95 and p1 to p99 instead of the usual p10 to p90. The results are presented in Online Appendix OA-1, and they show the same overall pattern as is presented in Figure 8.

Figure 8, panel (b) shows the time series of excess kurtosis for the distribution of residual log earnings growth rates. Generally, excess kurtosis is quite high indicating that the distribution of residual log earnings growth rates is leptokurtic, that is, has a high peak and heavy tails. The level of excess kurtosis tends to increase during periods with a low GDP growth rate and to decline during periods with a high GDP growth rate, but the cyclicality is not as pronounced as for skewness. The level and time series pattern of excess kurtosis and skewness is very similar for men and women.

3.2 *Heterogeneity by age and permanent income*

Figure 9 explores whether higher order moments, that is, dispersion, skewness, and excess kurtosis, of the distribution of residual log earnings growth rates vary across quantiles of permanent income and age groups, where permanent income is defined as the 3-year average earnings across income in period $t-2$, $t-1$, and t. Panels (a) and (b) show that dispersion is highest among individuals positioned at the lower end of the permanent income distribution. Young people tend to have more variable residual log earnings growth rates than older people, and this is more pronounced for women than for men.

Panels (c) and (d) of Figure 9 plot skewness across quantiles of permanent income and age groups. Skewness tends to be positive for low levels of permanent income and negative for high levels of permanent income. For men, there is hardly any difference across age groups, but for women, negative skewness is more pronounced for the youngest age group, ages 25–34, than for the other groups.

Panels (e) and (f) plot excess kurtosis along the same dimensions. Excess kurtosis tends to be more pronounced for low levels of permanent income and higher for the middle-aged and older subgroups. For women, excess kurtosis is not as concentrated at low levels of permanent income as for men.

3.3 *How moments of the distribution of residual log earnings growth rates vary across the business cycle*

In the graphical analysis presented so far, we have merely visually marked recession years in order to detect how the moments correlate with the business cycle. In this section, we further investigate this by examining how the 2nd, 3rd, and 4th moments of the distribution of residual log earnings growth rates are correlated with the log growth rate of GDP. In doing this, we follow Busch et al. (2022) and run regressions of each moment of the distribution of residual log earnings growth rates, denoted $m(g_t)$, on the log growth rate of GDP while controlling for a linear time trend:[6]

$$m(g_t) = \beta_0 + \beta_1 \Delta(\log GDP_t) + \gamma t + \varepsilon_t. \tag{1}$$

Consistent with the other analyses presented in this paper, we conduct the analysis separately for women and men. Table 2 summarizes the results. Dispersion for women is not significantly correlated with the log growth rate of GDP. Skewness is significantly correlated with the log growth rate of GDP, and this is the case for both men and women albeit the correlation is stronger for men. This confirms the impression from Figure 8 panel (a), that negative skewness is associated with recessions. Kurtosis does not correlate significantly with the log growth rate of GDP. These findings broadly resonate with the findings of Busch et al. (2022) who present similar regressions for Sweden, the US, and Germany.

[6]Note that g^1_{it} is forward looking, and in that spirit we also define the annual log growth rate of GDP as $\Delta(\log GDP_t) = \log GDP_{t+1} - \log GDP_t$. Both $\log GDP_t$ and $\Delta(\log GDP_t)$ are shown for the entire period in Appendix B.

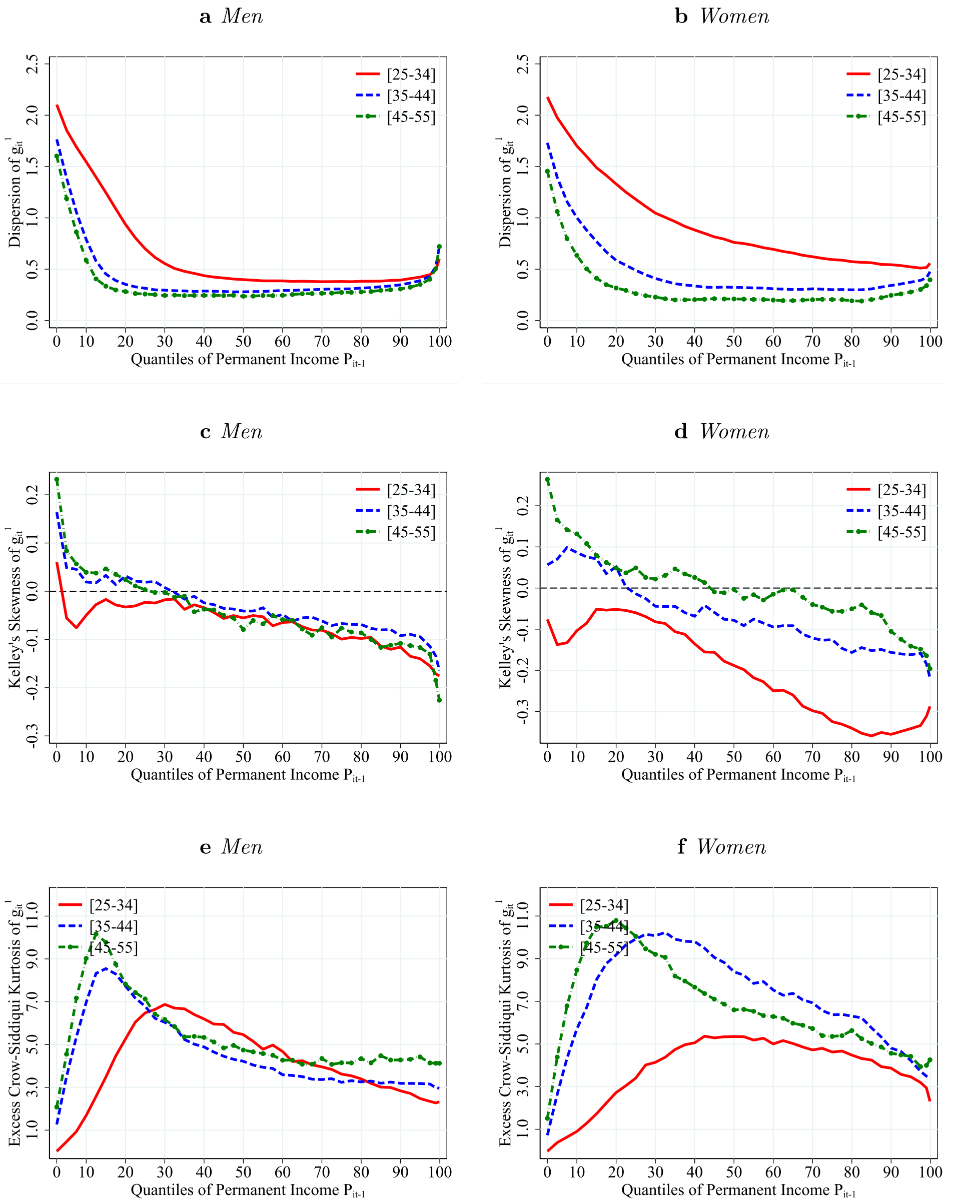

FIGURE 9. Dispersion, skewness, and kurtosis of the distribution of 1-year residual log earnings growth rates. *Notes*: Dispersion, skewness, and kurtosis of the distribution of 1-year residual log earnings growth rates, $g_{it}^1 = \varepsilon_{it+1} - \varepsilon_{it}$. H sample in the period 1997–2016. Permanent Income is based on three years of income, $t-2$, $t-1$, t. The figure plots the following variables against permanent income quantile groups for the 3 age groups (denoted by linetype): (a) Men: p90–p10, (b) Women: p90–p10, (c) Men: Kelley's skewness, (d) Women: Kelley's skewness, (e) Men: Excess Crow–Siddiqui kurtosis, (f) Women: Excess Crow–Siddiqui kurtosis. Kelley's skewness is calculated as $\frac{(\text{p90–p50})-(\text{p50–p10})}{\text{p90–p10}}$. Excess Crow–Siddiqui kurtosis is calculated as $\frac{\text{p97.5–p2.5}}{\text{p75–p25}} - 2.91$, where the first term is the Crow–Siddiqui measure of kurtosis, and 2.91 corresponds to the value of this measure for a normal distribution.

TABLE 2. Regression analysis of moments of the residual log earnings growth rate distribution on $\Delta(\log GDP_t)$ and a linear time trend.

Gender	Dispersion p90–p10	Kelley's Skewness	Excess Crow–Siddiqui Kurtosis
Men	−0.377	4.336	11.239
	(0.423)	(0.295)	(12.48)
Women	0.949	1.091	26.141
	(0.615)	(0.52)	(14.588)

Note: The table shows parameter estimates from regressions of moments of the residual log earnings growth distribution on the log growth rate of GDP. The regression also includes a linear time trend, but parameter estimates are not reported. Newey–West standard errors in parenthesis, maximum lag length: 3. LS sample. $\Delta(\log GDP_t)$ is annual. Dispersion is calculated as p90–p10, Kelley's skewness is calculated as $\frac{(p90-p50)-(p50-p10)}{p90-p10}$. Excess Crow–Siddiqui kurtosis is calculated as $\frac{p97.5-p2.5}{p75-p25}$ − 2.91, where the first term is the Crow–Siddiqui measure of kurtosis, and 2.91 corresponds to the value of this measure for a normal distribution.

Online Appendix OA-2 explores how dispersion, skewness, and excess kurtosis are correlated with the log growth rate of GDP across selected quantiles of the permanent income distribution, where permanent income at time t is defined as average earnings over $t-2$, $t-1$, and t. This is done by graphically presenting estimates of β_1 obtained by running equation (1) separately by quantiles of permanent income and for three age groups. While the overall correlation between dispersion and the log growth rate of GDP is not significant, dispersion for women belonging to the bottom half of the permanent income distribution is high, particularly for youngest age group, age 25–34. The correlation between skewness and the log growth rate of GDP is clearly driven by the bottom end of the permanent income distribution and it is more pronounced among men than women as also indicated by the overall regression results presented in Table 2. The correlation for excess kurtosis is negative for men, and mostly so for men belonging to the lower end of the distribution of permanent income. However, the excess kurtosis estimates are not significantly different from zero, which is consistent with the overall results presented in Table 2.

3.4 *Earnings mobility*

An important aspect of inequality is mobility, that is, how people move across the distribution of earnings. The final set of statistics presented in this section summarizes this. Figure 10 presents 10-year mobility statistics based on permanent income, which is defined as 3-year average earnings. The rank-position in the permanent income distribution is on the horizontal axis, and the corresponding rank-position 10 years later is on the vertical axis. The solid line shows mobility for 25–34 year olds (in the base year) and the dashed line shows mobility for 35–44 year olds. The closer the mobility measure is positioned to the diagonal the less mobility there is. The graphs generally show that there is some degree of mobility, particularly at the bottom of the initial distribution. Mobility is most pronounced at young ages, reflecting a life-cycle pattern with increasing earnings levels at the beginning of the working life. The pattern is similar for men and women, and it is very stable across time; cf., Figure 11 showing that the mobility measures are practically identical whether calculated using 1995 or 2005 as the base year.

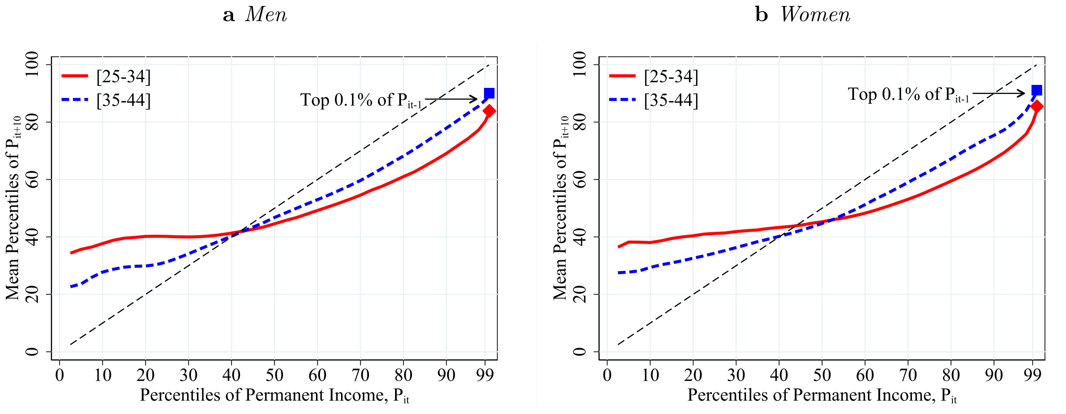

FIGURE 10. Evolution of 10-year mobility over the life cycle. *Notes*: The figure shows average rank-rank for men and women and for different age groups. H sample and observed at both t and t+10. Permanent income is based on 3 years of income, $t-2$, $t-1$, t. The black diagonal dashed line is the 45-degree line inserted to indicate what would be expected if there is no mobility.

3.5 *Summary of part 1*

Overall earnings inequality in Denmark has increased over the period 1987–2016 when considering the level of earnings. Earnings inequality is most predominant in the bottom half of the distribution where the dispersion is almost double that of the top half. Also, while inequality in the bottom half of the distribution is business cycle dependent, it is very stable in the top half.

The picture for earnings dynamics, that is, the residual log earnings growth rate looks different. The dispersion of the distribution of residual log earnings growth rates is sim-

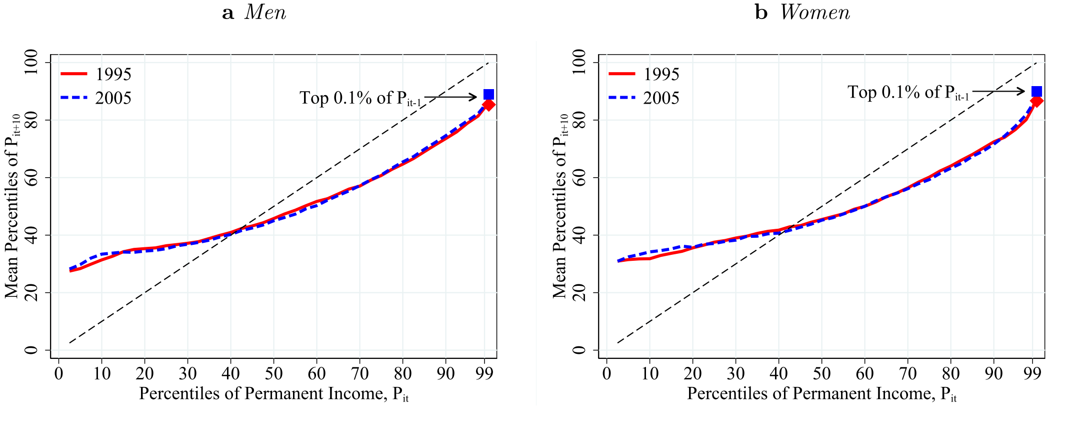

FIGURE 11. Evolution of 10-year mobility over time. *Notes*: The figure shows average10-year rank-rank for men and women and for different baseline years. H sample and observed at both t and t+10. Permanent income is based on 3 years of income, $t-2$, $t-1$, t. The solid line uses 1995 as the base year and the dashed line uses 2005 as the base year. The black diagonal dashed line is the 45-degree line inserted to indicate what would be expected if there were no mobility.

ilar for the top and the bottom half of the distribution. The distribution of residual log earnings growth rates exhibits skewness that covaries positively with the business cycle, and significant excess kurtosis. Generally, higher dispersion, positive skewness, and excess kurtosis are most pronounced at the lower end of the permanent income distribution.

Related to this, income mobility is significant and mostly so among the young and among those positioned in the lower end of the distribution of earnings. A person positioned at the 10th percentile will, on average, be positioned at the 35th percentile 10 years later, and a person positioned at the 90th percentile will, on average, be positioned at the 75th percentile 10 years later. Earnings mobility has been stable across the observation period. Finally, one remarkable feature of the Danish case is that the patterns are very similar across men and women, and this is the case for almost all of the metrics considered in this analysis.

4. Trends in the inequality and dynamics of disposable income

The previous section focused on selected aspects of the level of inequality as well as on the distributional properties of earnings dynamics, that is, the moments of the distribution of residual log earnings growth rates. In this section, we will consider the same aspects, but for disposable income instead. Studying how the properties of income dynamics change when considering disposable income rather than earnings is of interest because it documents the degree to which the welfare state is able to insulate its citizens from earnings fluctuations. Denmark is an ideal case for studying exactly this dimension for two reasons. First, both types of income are documented in the Danish administrative data. Second, Denmark has a high level of redistribution and is an example of a country where the properties of earnings and disposable income dynamics are likely to be different.

In Denmark, income is taxed individually.[7] We define individual disposable income as *All personal income—taxes—interest payments—alimony*, where personal income includes earnings (including income from self-employment), transfers, capital income, and pensions. The disposable income in 1995 and 2005 is summarized in Table 3. For the lowest percentiles (p1, p5, p10) of disposable income, the values are larger compared to earnings, but for the remaining percentiles, the values are lower, illustrating the effects of both transfers and taxes. Moreover, the level of disposable income for women is about 15% lower than for men, thus muting the gap observed for earnings in Table 1. From 1995 to 2015, average disposable income increased 35–39%. This is a larger increase than for earnings, and it is consistent with the general reduction in tax rates at all income levels.

Selected percentiles of the level of log disposable income are shown in Figure 12, which is directly comparable to Figure 2. The level of income at the lower end, p10, fluctuates less than for earnings for both men and women, suggesting a strong insurance

[7] It is possible to transfer some unutilized allowances between spouses. We summarize tax payments after such unutilized allowances has been transferred, that is, we use the actual tax payments recorded at the individual level. This is, in practice, only important for couples where one spouse has very limited income. In Online Appendix OA-6, we redo the analysis at the household level.

Table 3. Summary statistics for different samples, disposable income.

Year	Obs. (Mill)	Mean Disposable Income: Men	Mean Disposable Income: Women
1995	1.85	32,112	28,141
2015	1.82	44,786	38,058

Year	P1	P5	P10	P25	P50	P75	P90	P95	P99	P99.9
1995	10,880	16,516	19,964	24,277	28,711	33,924	40,388	46,320	67,573	150,318
2015	10,108	17,432	22,515	30,142	37,589	46,772	58,815	70,218	120,120	376,143

Note: The table shows selected summary statistics for the sample for 1995 and 2015 for disposable income. All monetary values are summarized in US dollars by converting 2018 Danish Kroner values to US dollars using yearly exchange rates.

effect of the transfer system. Panels (a) and (b) show that all levels of log disposable income evolved almost exactly in parallel until around 2005, when they start to fan out. Panels (c) and (d) show the development of log disposable income at the top end of the distribution. The development here resembles that of earnings (cf., Figure 2) with the exception that log disposable income at the very top is more volatile. Overall, Figure 12 shows that inequality in the level of log disposable income increased over the period considered. In particular, disposable income at the bottom-end of the distribution increased 20–30% relative to its 1987 level.

Figure 13 measures the dispersion of log disposable income. Panels (a) and (b) present $2.56\times\sigma$, and the distance between the 90th and the 10th percentile in the distribution, p90–p10. Overall, the dispersion of log disposable income increased over the observation period but only moderately so compared to earnings. Also, the level of dispersion of log disposable income is significantly smaller than for earnings; cf. Figure 3. For example, in 2016, the dispersion of log earnings is more than 50% higher than it is for log disposable income. Panels (c) and (d) present the difference between the 90th percentile and the median, p90–p50, and the difference between the median and the 10th percentile, p50–p10. They show that the dispersion in the interval p90–p10 is about the same above and below the median. This pattern is different from that observed for earnings where dispersion is clearly higher for the lower part of the distribution.

Figure 14 plots the life-cycle paths of log disposable income for four selected birth cohorts. The solid lines track the within-cohort earnings dispersion, measured by the p90–p10 distance, across time, and the dashed lines track the dispersion for people at different ages, 25, 30, 35, and 40. The figure shows that the dispersion of log disposable income is practically constant over the life cycle.[8] This is quite different from earnings where dispersion is high at young ages but declines with age.

[8]In Online Appendix OA-3, we plot separately the life-cycle pattern of dispersion of log disposable income for the upper, p90–p50, and lower, p50–p10, part of the distribution. For both of these, dispersion is approximately constant over the life cycle.

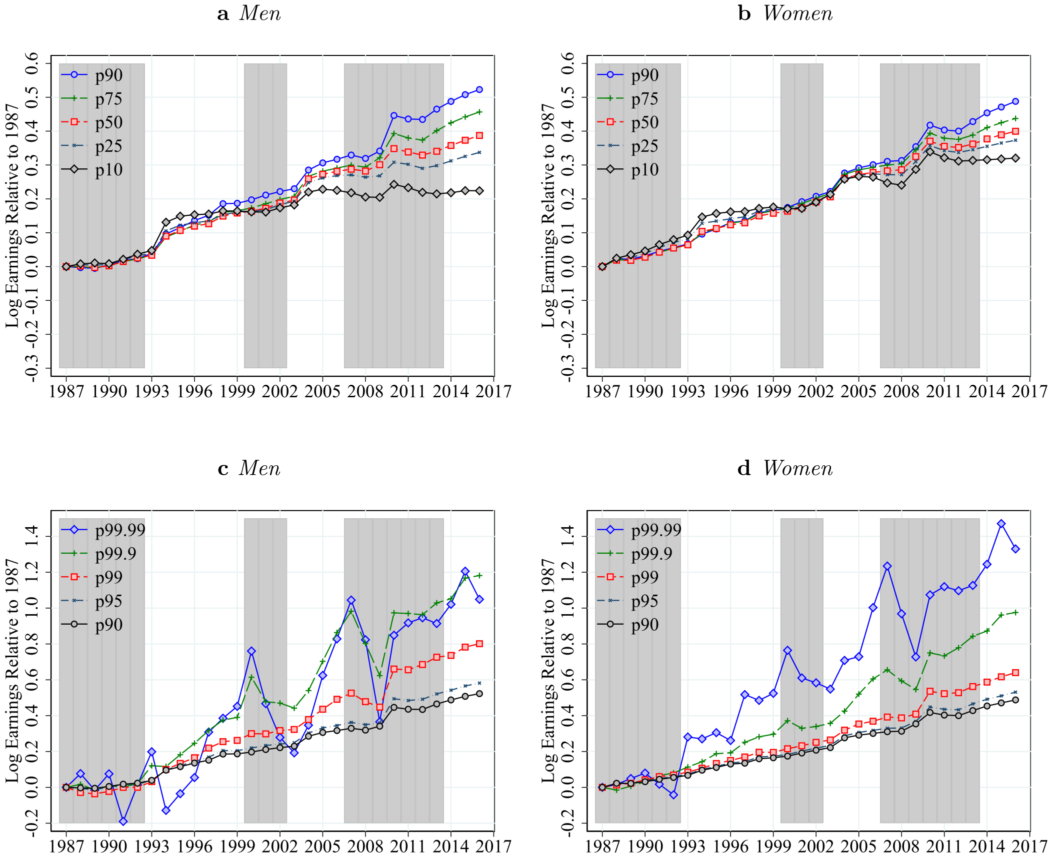

FIGURE 12. Percentiles of the distribution of log disposable income. *Notes*: The figure plots raw log disposable income for selected percentiles where all percentiles are normalized to 0 in the first available year. CS sample. The figure plots the following variables against time: (a) Men: p10, p25, p50, p75, p90 (b) Women: p10, p25, p50, p75, p90, (c) Men: p90, p95, p99, p99.9, p99.99, (c) Women: p90, p95, p99, p99.9, p99.99. The shaded areas indicate recessionary periods with GDP growth rate below 2%.

4.1 *Growth rate dynamics for disposable income*

In this section, we first present key moments for the distribution of residual log disposable income growth rates that are directly comparable to the results for earnings presented in the previous section. Second, we examine both heterogeneity and the relationship between growth rates and the business cycle.

In Figure 15, we show total dispersion, top dispersion, and bottom dispersion for the distribution of residual log disposable income growth rates for men and women. The figure shows at least two interesting patterns compared to the evidence presented for earnings in Figure 7. First, the level of overall dispersion is considerably lower at around 0.4 (compared to 0.5–0.7). This is consistent with the fact that disposable income is a result of considerable redistribution through the tax and transfer systems. Another interesting difference is that the dispersion of the distribution of residual log disposable

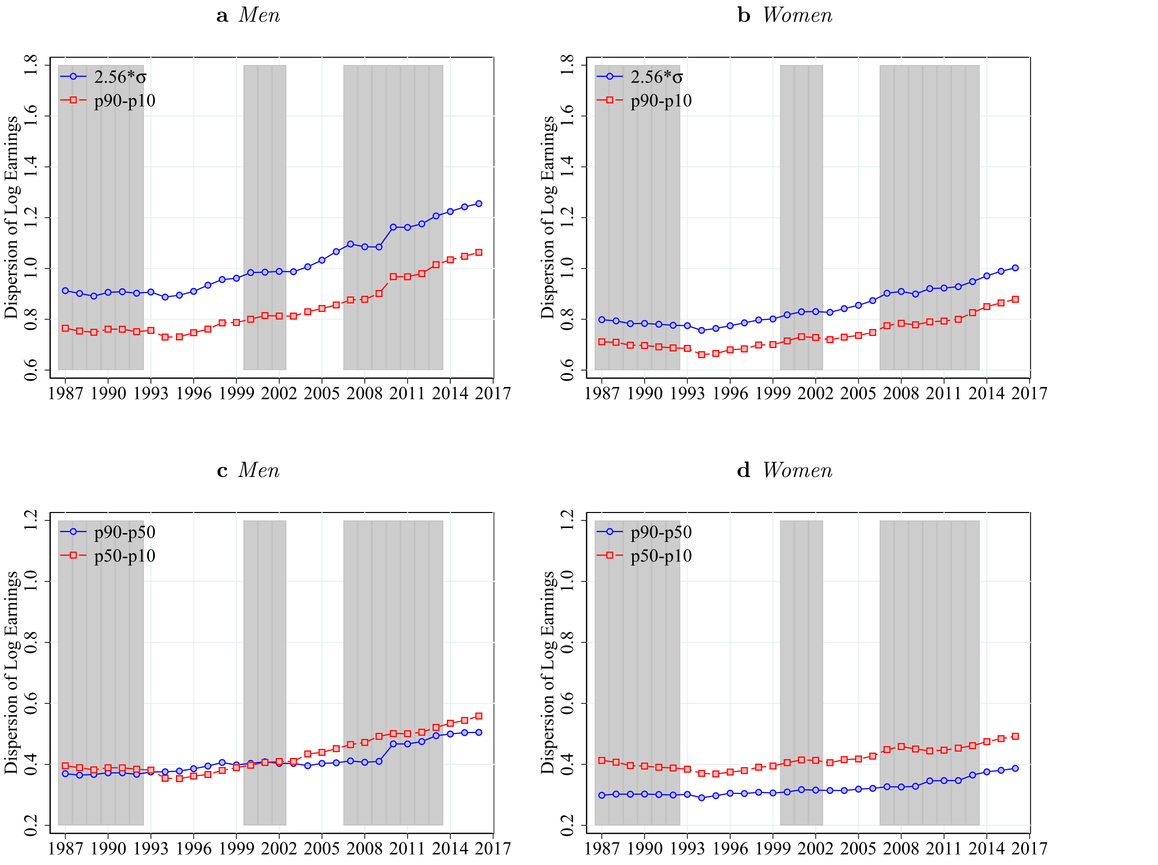

FIGURE 13. Income inequality, log disposable income. *Notes*: The figure plots dispersion of raw log disposable income. CS sample. The following variables are plotted against time: (a) Men: p90–p10 and 2.56*σ of log earnings, where σ is the standard deviation (b) Women: p90–p10 and 2.56*σ of log earnings (c) Men: p90–p50 and p50–p10, (d) Women: p90–p50 and p50–p10. The shaded areas indicate recessionary periods with the GDP growth rate below 2%. 2.56*σ corresponds to the p90–p10 differential for a normal distribution.

income growth rates is very stable over the three decades considered compared to the distribution of residual log earnings growth rates. Apart from this, some patterns are similar when comparing the dispersion of the distribution of residual log disposable income growth rates and the distribution of residual log earnings growth rates: The dispersion in the top and bottom half is similar and the dispersion for men and women is also similar.

Figure 16 shows how skewness and excess kurtosis has developed for the distribution of residual log disposable income growth rates. The figure corresponds to Figure 8 for the distribution of residual log earnings growth rates. It shows that skewness is quite small and relatively stable across time, that is, with very limited business-cycle variation,

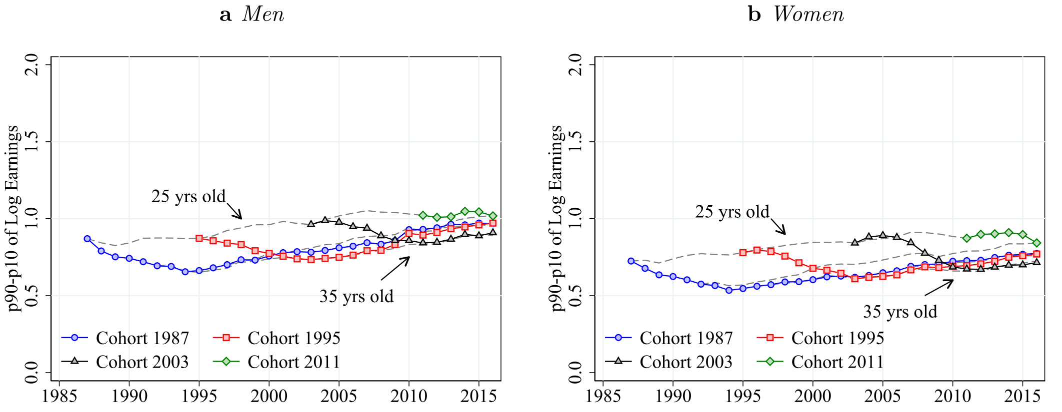

FIGURE 14. Life-cycle inequality over cohorts, log disposable income. *Notes*: The figure plots life-cycle profiles of dispersion of raw log disposable income. CS sample. The following variables are plotted against time: (a) Men: p90–p10 over the life cycle for four selected cohorts (indexed by age 25), (b) Women: p90–p10 over the life cycle for four selected cohorts (indexed by age 25).

for both men and women.[9] Similarly, excess kurtosis is very stable at a level of about 4, about one-third of the level of excess kurtosis for the distribution of residual log earnings growth rates.

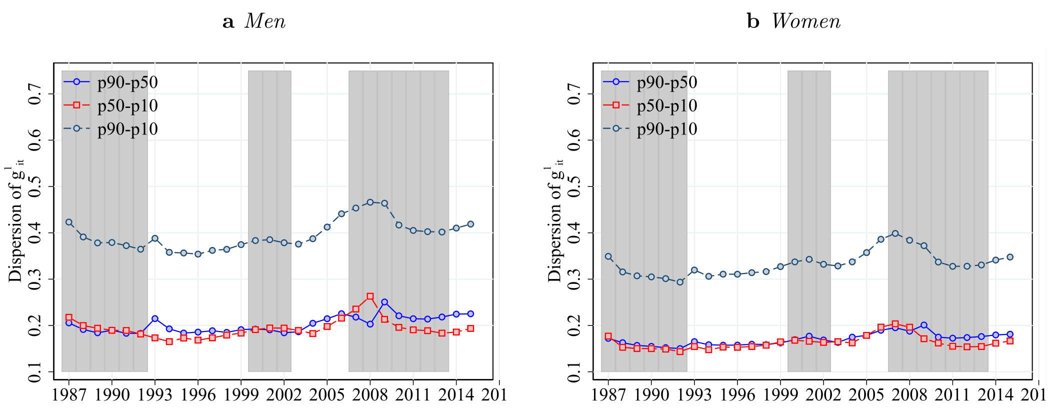

FIGURE 15. Dispersion of 1-year residual log disposable income growth. *Notes*: Dispersion of 1-year residual log disposable income growth, $g_{it}^1 = \varepsilon_{it+1} - \varepsilon_{it}$. LS sample. The figure plots the following variables against time: p90–p50 (solid), p50–p10 (long dash), and p90–p10 (short dash) for men in panel a, and for women in panel b. The shaded areas indicate recessionary periods with GDP growth below 2%.

[9]Results based on alternative definitions of Kelley's skewness that take more of the income distribution into account by spanning p5 to p95 and p1 to p99 instead of the usual p10 to p90 are reported in Online Appendix OA-1, and they show the same overall pattern as is presented in Figure 16.

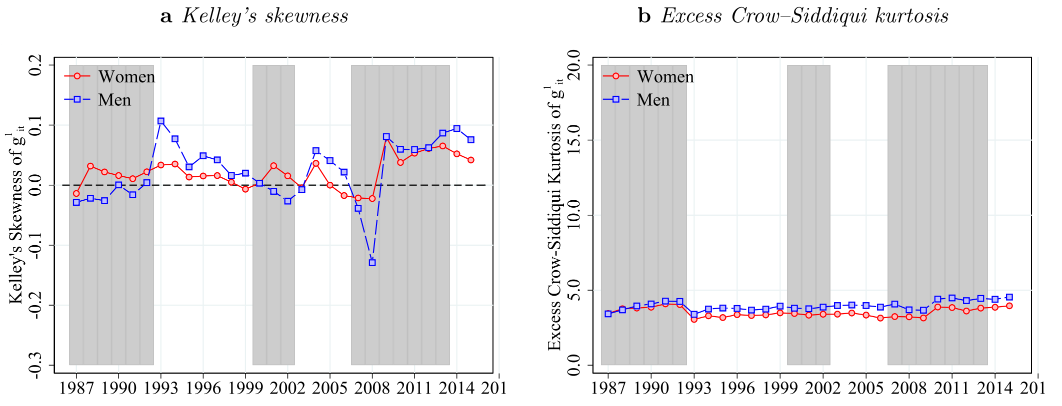

FIGURE 16. Skewness and kurtosis of 1-year residual log disposable income growth. *Notes*: Skewness and kurtosis of 1-year residual log disposable income growth, $g_{it}^1 = \varepsilon_{it+1} - \varepsilon_{it}$. LS sample. The figure plots the following variables against time: (a) Men and Women: Kelley's skewness calculated as $\frac{(\text{p90–p50})-(\text{p50–p10})}{\text{p90–p10}}$, (b) Men and Women: Excess Crow–Siddiqui kurtosis calculated as $\frac{\text{p97.5–p2.5}}{\text{p75–p25}} - 2.91$ where the first term is the Crow–Siddiqui measure of kurtosis and 2.91, corresponds to the value of this measure for a normal distribution. The shaded areas indicate recessionary periods with GDP growth below 2%.

4.2 *Heterogeneity by age and permanent income*

Figure 9 showed evidence that dispersion, skewness, and excess kurtosis for the distribution of residual log earnings growth rates were heterogeneous across permanent income levels and, to some extent, also across age groups. Figure 17 shows the corresponding pictures for residual log disposable income growth. The overall impression is quite different. A first thing to notice is that the patterns for all three statistics are similar across age groups and across gender. There is some heterogeneity across levels of permanent income, but the heterogeneity is much less pronounced than for residual log earnings growth rates. The dispersion is larger at the extreme ends of the income distribution, but otherwise quite homogeneous. Skewness is somewhat different. Here, we find evidence that those with the lowest levels of income face a distribution of residual log disposable income growth with positive skewness and that individuals at the upper end face a distribution with negative skewness. The level of skewness is, however, moderate at all levels of income. Finally, the two bottom panels of Figure 17 show that excess kurtosis is practically constant and at a much lower level than for the distribution of residual log earnings growth rates.

4.3 *How moments of residual log disposable income growth vary across the business cycle*

Figures 15 and 16 suggest that the moments (dispersion, skewness, and excess kurtosis) of the distribution of residual log disposable income growth rates are far less business-cycle dependent than is the case for the distribution of residual log earnings growth rates. To investigate this further, we run regressions of these moments on the log growth

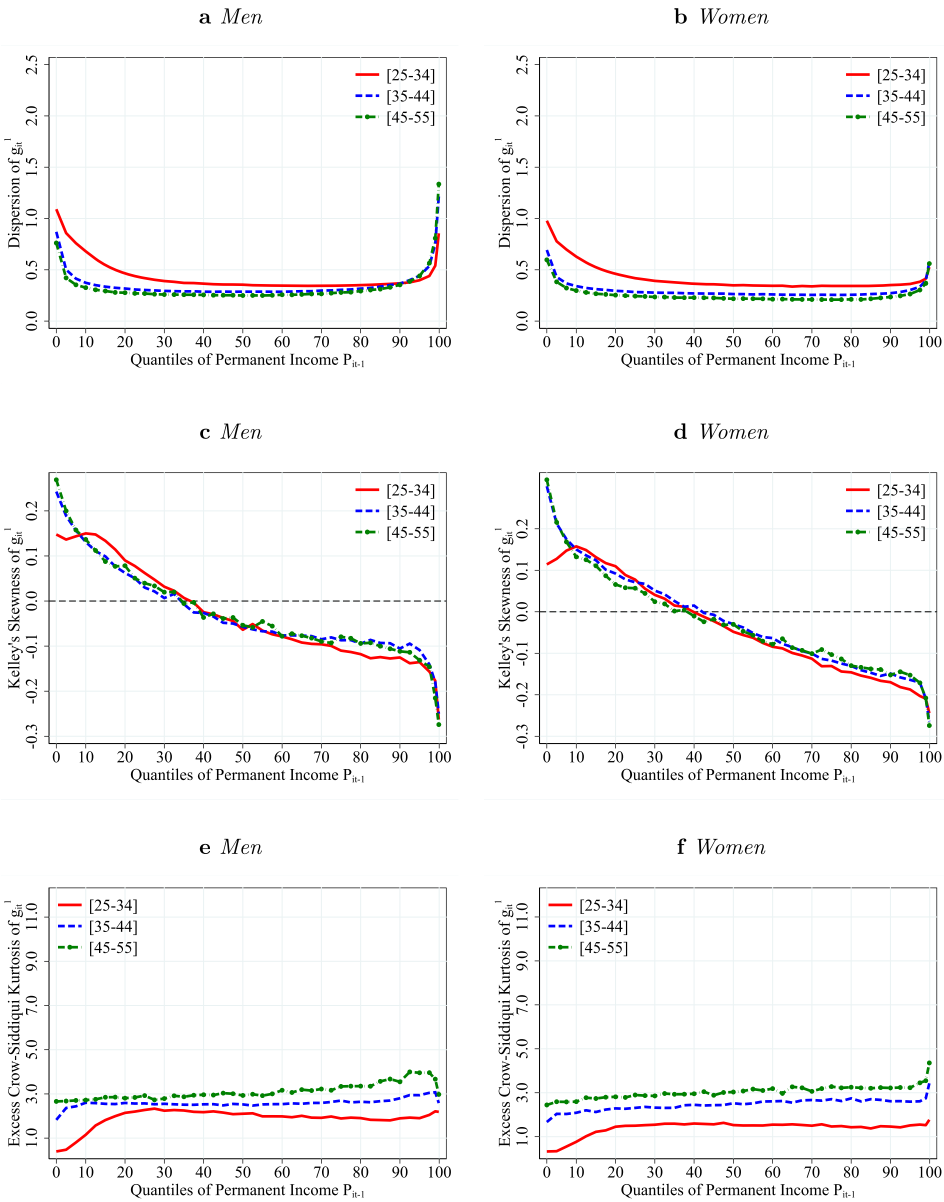

FIGURE 17. Dispersion, skewness, and kurtosis of 1-year residual log disposable income growth. *Notes*: Dispersion, skewness, and kurtosis of 1-year residual log disposable income growth, $g^1_{it} = \varepsilon_{it+1} - \varepsilon_{it}$. H sample in the period 1997–2016. Permanent Income is based on three years of income, $t-2$, $t-1$, t. The figure plots the following variables against permanent income quantile groups for the 3 age groups (denoted by linetype): (a) Men: p90–p10, (b) Women: p90–p10, (c) Men: Kelley's skewness, (d) Women: Kelley's skewness, (e) Men: Excess Crow–Siddiqui kurtosis, (f) Women: Excess Crow–Siddiqui kurtosis. Kelley's skewness is calculated as $\frac{(\text{p90}-\text{p50})-(\text{p50}-\text{p10})}{\text{p90}-\text{p10}}$. Excess Crow–Siddiqui kurtosis is calculated as $\frac{\text{p97.5}-\text{p2.5}}{\text{p75}-\text{p25}} - 2.91$, where the first term is the Crow–Siddiqui measure of kurtosis, and 2.91 corresponds to the value of this measure for a normal distribution.

Table 4. Regression analysis of moments of the residual log disposable income growth distribution on $\Delta(\log GDP_t)$ and a linear time trend.

Gender	Dispersion p90–p10	Kelley's Skewness	Excess Crow–Siddiqui Kurtosis
Men	−0.749	2.154	0.877
	(0.244)	(0.302)	(3.405)
Women	−0.499	0.433	−1.019
	(0.209)	(0.229)	(4.523)

Note: The table shows parameter estimates from regressions of moments of the residual log disposable income growth distribution on the log growth rate of GDP. The regression also includes a linear time trend, but parameter estimates are not reported. Newey–West standard errors in parenthesis, maximum lag length: 3. LS sample. $\Delta(\log GDP_t)$ is annual. Dispersion is calculated as p90–p10. Kelley's skewness is calculated as $\frac{(p90--p50)-(p50--p10)}{p90--p10}$. Excess Crow–Siddiqui kurtosis is calculated as $\frac{p97.5--p2.5}{p75--p25} - 2.91$, where the first term is the Crow–Siddiqui measure of kurtosis, and 2.91 corresponds to the value of this measure for a normal distribution.

rate of GDP and a linear time trend, similar to equation (1) in Section 3.3. Table 4 summarizes the results. Dispersion is significantly negatively correlated with the log growth rate of GDP. In unreported regressions, we find that the significant correlation between the dispersion of the distribution of log residual disposable income growth rates and the log growth rate of GDP is entirely driven by the observation for 2008, which is a year with particularly strong negative GDP growth; cf. Appendix B. Skewness is still significantly correlated with the log growth rate of GDP for men, but the magnitude of the correlation is about one-half of that of the distribution of residual log earnings growth rates, and the correlation is not significant for women. Kurtosis is not significantly correlated with the log growth rate of GDP. Overall, we find that the correlations between moments of the distribution of residual log disposable income growth rates and log growth rate of GDP are generally smaller than for the moments of the distribution of residual log earnings growth rates (shown in Table 2).

In Online Appendix OA-2, we explore how the correlation between moments of residual log disposable income growth and the log growth rate of GDP vary over quantiles of the permanent income distribution and age groups. As in Section 3.3, this is done by graphically presenting estimates of β_1 obtained by running equation (1) separately by quantiles of permanent income and for three age groups. The results show that there is practically no heterogeneity across levels of permanent income in the correlation between the moments of the distribution of residual log disposable income growth and the log growth rate of GDP. This suggests that the tax and transfer systems are effectively able to iron out most of the variation induced by business-cycle fluctuations.

4.4 *Other income measures*

The results presented so far suggest that the properties of the distribution of residual log disposable income growth are quite different to the properties of the distribution of residual log earnings growth rates. This could have been caused by tax collection and/or by transfer income, such as unemployment insurance benefits. In Online Appendix OA-4, we present figures corresponding to Figures 15–17 based on residual log gross income, that is, total income before taxes are deducted. The properties of the distribution of residual log gross income growth rates are quite similar to the properties of the distribution of residual log disposable income growth rates, with dispersion, and skewness measures being almost identical. Kurtosis is also very stable for the distribution of residual log gross income growth rates across the observation period but at a higher level.

Next, we repeat the analysis at the household level. First, we consider the distribution of household level residual log earnings growth rates. The results from this analysis are presented in Online Appendix OA-5. Results are presented in per capita terms, that is, household income is split evenly among household members, and the results are considered at the individual level in order to make them comparable across single and dual adult households. Next, we consider household residual log disposable income growth rates in Online Appendix OA-6. The results are strikingly similar to the results for individuals. This is indicative that very little insurance takes places within the household. These findings are consistent with Lau Andersen, Jensen, Johannesen, Thustrup Kreiner, Leth-Petersen, and Sheridan (2021) who show that the added-worker effect is not important in Denmark in relation to unemployment events. This is likely due to the fact that both male and female labor market participation rates are very high and the potential for increasing labor supply is limited.

Finally, we consider whether our findings only characterize short term income fluctuations. We do this using 5-year growth rates of residual log earnings and disposable income. The results for earnings are shown in Online Appendix OA-7 and those for disposable income are shown in Online Appendix OA-8. The dispersion of the distribution of 5-year residual log earnings growth rates is about double that of the distribution of 1-year residual log earnings growth rates, suggesting that earnings changes are persistent. Skewness is largely unchanged and excess kurtosis is smaller, suggesting that there are fewer extreme earnings changes at the 5-year horizon than at the 1-year horizon. Comparing the distribution of 5-year residual log disposable income growth rates to the distribution of 1-year residual log disposable income growth rates, we find a similar pattern, albeit all moments of the distribution of residual log disposable income growth rates are muted relative to their counterparts based on earnings. These findings tell us that the tax and transfer systems are able to mute the impact of changes in earnings not only in the very short term but also in the medium to long term.

4.5 *Summary of part 2*

The distribution of the level of log disposable income is different to that of earnings. Overall, disposable income has grown for most people, even for the lower part of the distribution. Interestingly, the level of income has grown more for the disposable income distribution than for the earnings distribution. This is consistent with a sequence of tax reforms that have lowered the marginal income tax rate significantly. Moreover, the dispersion of log disposable income is almost constant over the life cycle. This is contrary to earnings, and it indicates that the tax and transfer systems are able to effectively mute life-cycle inequality.

The properties of disposable income dynamics, that is, residual log disposable income growth rates, are also quite different to those of earnings. As a consequence of significant and progressive income taxation in Denmark and relatively generous UI benefits, the dispersion of the distribution of residual log disposable income growth rates is about two-thirds of that of the distribution of residual log earnings growth rates. The distribution of residual log disposable income growth rates has practically no skewness and exhibits much less excess kurtosis than the distribution of residual log earnings growth rates. Moreover, dispersion, skewness, and excess kurtosis of the distribution of residual log disposable income growth rates are remarkably stable over the three decades considered. The patterns for the distribution of household level residual log disposable income growth rates are, for all practical purposes, identical to the patterns for the distribution of individual level residual log disposable income growth rates, suggesting that insurance within the household is not important in the Danish context. Overall, these results suggest that the tax and transfer income systems play the all dominating role in reducing the impact of earnings fluctuations on disposable income. All results are similar for men and women.

5. Conclusion

This paper documents facts about the distribution of earnings and disposable income growth rates in Denmark over the period 1987–2016. This is done by analyzing administrative register data covering the entire Danish population. The administrative data include information about earnings as well as gross income and disposable income, and we are able to construct household units by linking to the population register. We use this information to document a number of facts.

First, we document that the distribution of residual log earnings growth rates exhibits pro-cyclical skewness and excess kurtosis. Second, the properties of the distribution of residual log earnings growth rates appear to be practically the same for men and women. This is likely due to the fact that education levels are similar and the female labor force participation rate has been high in Denmark throughout the observation period. Furthermore, we find that the properties of the distribution of household level residual log earnings growth rates are similar to those of the distribution of individual level residual log earnings growth rates, indicating that the added-worker effect is not important in the Danish context. Third, we find that the properties of the distribution of residual log disposable income growth rates are quite different to the properties of the distribution of residual log earnings growth rates. The dispersion of the distribution of residual log disposable income growth rates is about two-thirds of that of earnings, and the distribution of residual log disposable income growth rates has practically no skewness and exhibits much less excess kurtosis than the distribution of residual log earnings growth rates. Finally, dispersion, skewness, and excess kurtosis of the distribution of residual log disposable income growth rates are remarkably stable over the three decades considered. These results suggest that the tax and transfer systems are quite effective in reducing the impact of the fluctuations in earnings that people in Denmark face.

Appendix A: Results for the whole sample

a *Whole sample* **b** *Whole sample*

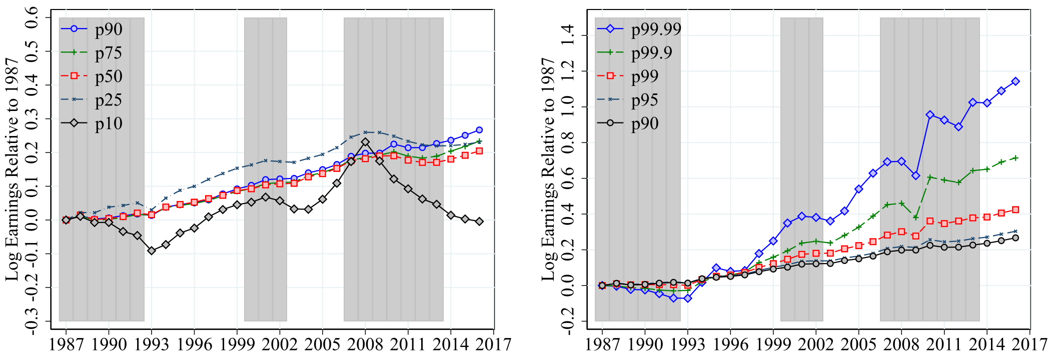

Figure 18. Change of percentiles of the log real earnings distribution. *Notes*: The figure plots raw log earnings for selected percentiles where all percentiles are normalized to 0 in the first available year. CS sample. The figure plots the following variables against time: (a) Whole sample: p10, p25, p50, p75, p90, (b) Whole sample: p90, p95, p99, p99.9, p99.99. The shaded areas indicate recessionary periods where the annual GDP growth rate is below 2%.

a *Whole sample* **b** *Whole sample*

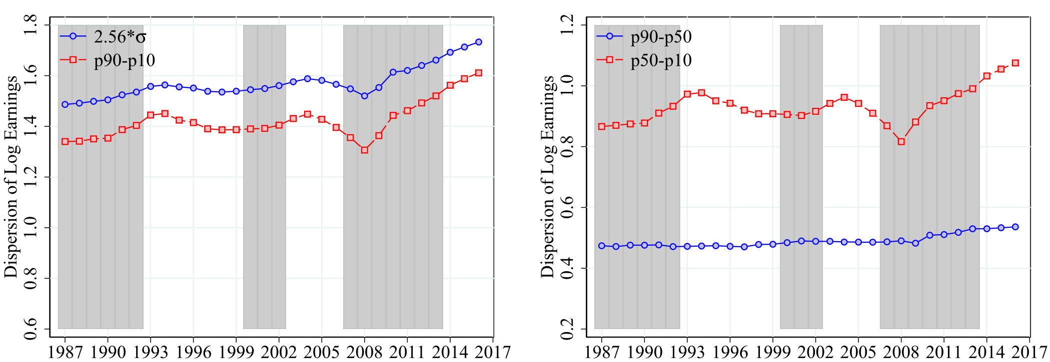

Figure 19. Earnings inequality. *Notes*: The figure plots dispersion of raw log earnings. CS sample. The following variables are plotted against time: (a) Whole sample: p90–p10 and 2.56*σ of log earnings, where σ is the standard deviation. (b) Whole sample: p90–p50 and p50–p10. The shaded areas indicate recessionary periods where annual GDP growth rate is below 2%. 2.56*σ corresponds to the p90–p10 differential for a Gaussian distribution.

a *Whole sample*

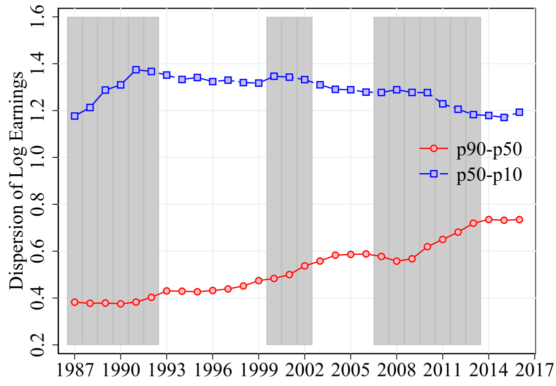

FIGURE 20. Income inequality at age 25. *Notes*: The figure plots dispersion of raw log earnings. CS sample at age 25. The following variable is plotted against time: (a) Whole sample: p90–p50 and p50–p10. The shaded areas indicate recessionary periods where annual GDP growth rate is below 2%.

a *Whole sample*

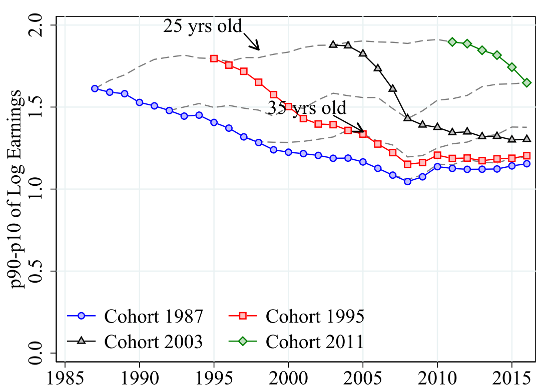

FIGURE 21. Life-cycle inequality over cohorts. *Notes*: The figure plots life-cycle profiles of dispersion of raw log earnings. CS sample. The following variable is plotted against time: (a) Whole sample: p90–p10 over the life cycle for four selected cohorts (indexed by age 25).

a *Whole sample* **b** *Whole sample*

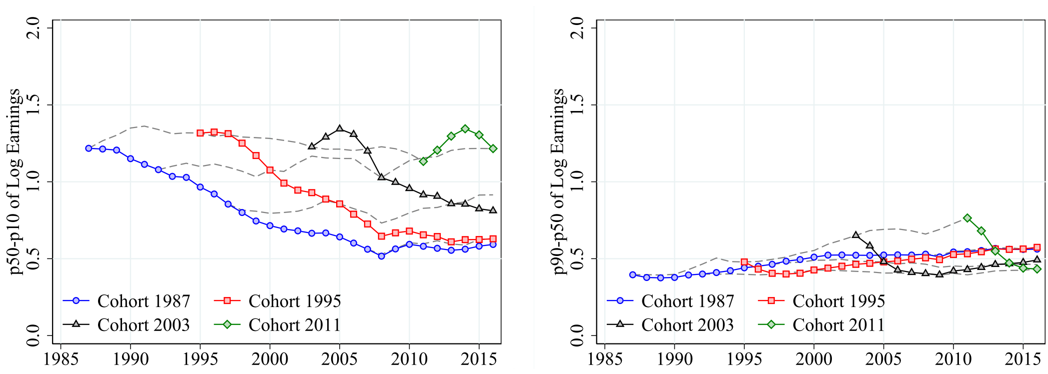

FIGURE 22. Life-cycle inequality over cohorts for above and below median income. *Notes*: The figure plots life-cycle profiles of dispersion of raw log earnings. CS sample. The following variables are plotted against time over the life cycle for four selected cohorts (indexed by age 25): (a) Whole sample: p50–p10, (b) Whole sample: p90–p50.

a *Whole sample*

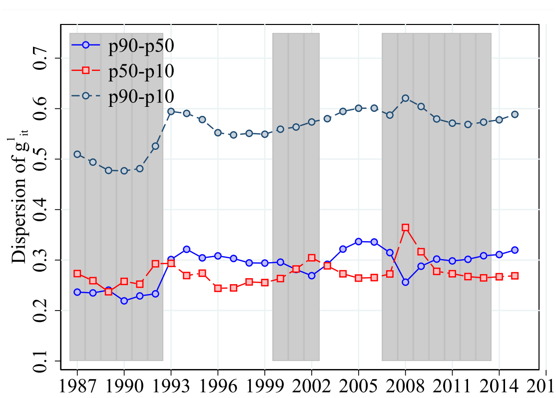

FIGURE 23. Dispersion of the distribution of 1-year residual log earnings growth rates. *Notes*: Dispersion of 1-year residual log earnings growth rate, $g_{it}^1 = \varepsilon_{it+1} - \varepsilon_{it}$. LS sample. The figure plots the following variables against time: p90–p50 (solid), p50–p10 (long dash), and p90–p10 (short dash). The shaded areas indicate recessionary periods with GDP growth below 2%.

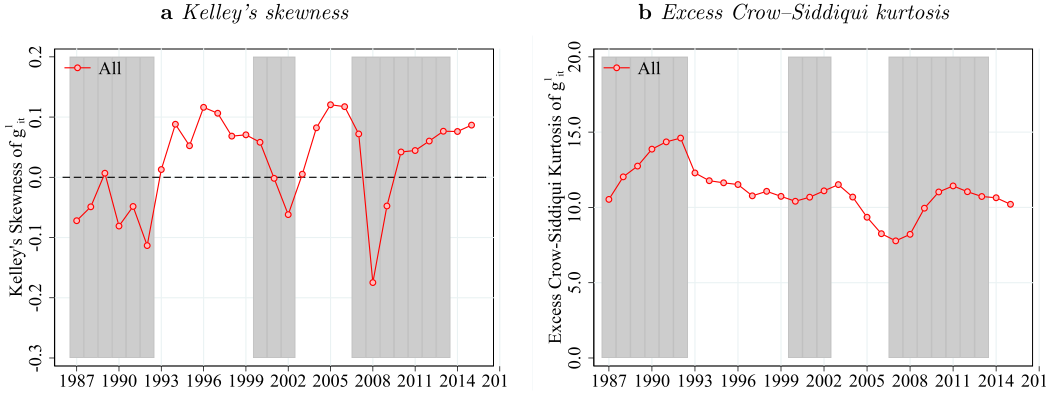

FIGURE 24. Skewness and kurtosis of the distribution of 1-year residual log earnings growth rates. *Notes*: Skewness and kurtosis of the distribution of 1-year residual log earnings growth rates, $g^1_{it} = \varepsilon_{it+1} - \varepsilon_{it}$. LS sample. The figure plots the following variables against time: (a) Whole sample: Kelley's skewness calculated as $\frac{(\text{p90–p50})-(\text{p50–p10})}{\text{p90–p10}}$, (b) Whole sample: Excess Crow–Siddiqui kurtosis calculated as $\frac{\text{p97.5–p2.5}}{\text{p75–p25}} - 2.91$ where the first term is the Crow–Siddiqui measure of kurtosis and 2.91, corresponds to the value of this measure for a normal distribution. The shaded areas indicate recessionary periods with GDP growth below 2%.

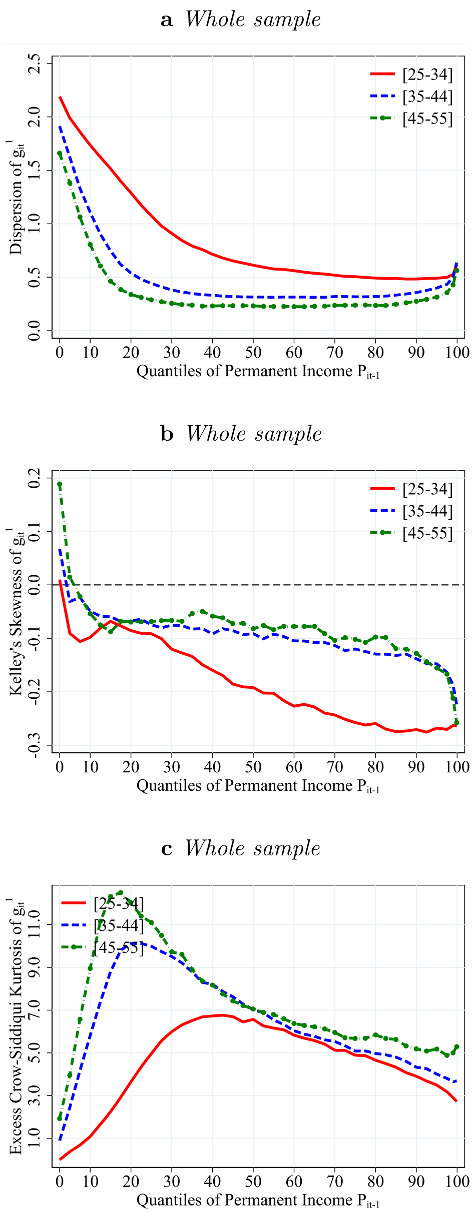

FIGURE 25. Dispersion, skewness, and kurtosis of the distribution of 1-year residual log earnings growth rates. *Notes*: Dispersion, skewness, and kurtosis of the distribution of 1-year residual log earnings growth rates, $g_{it}^{1} = \varepsilon_{it+1} - \varepsilon_{it}$. H sample in the period 1997–2016. Permanent income is based on 3 years of income, $t-2$, $t-1$, t. The figure plots the following variables against permanent income quantile groups for the 3 age groups (denoted by linetype): (a) Whole sample: p90–p10, (b) Whole sample: Kelley's skewness, (c) Whole sample: Excess Crow–Siddiqui kurtosis. Kelley's skewness is calculated as $\frac{(\text{p90–p50})-(\text{p50–p10})}{\text{p90–p10}}$. Excess Crow–Siddiqui kurtosis is calculated as $\frac{\text{p97.5–p2.5}}{\text{p75–p25}} - 2.91$, where the first term is the Crow–Siddiqui measure of kurtosis, and 2.91 corresponds to the value of this measure for a normal distribution.

Appendix B: GDP in Denmark

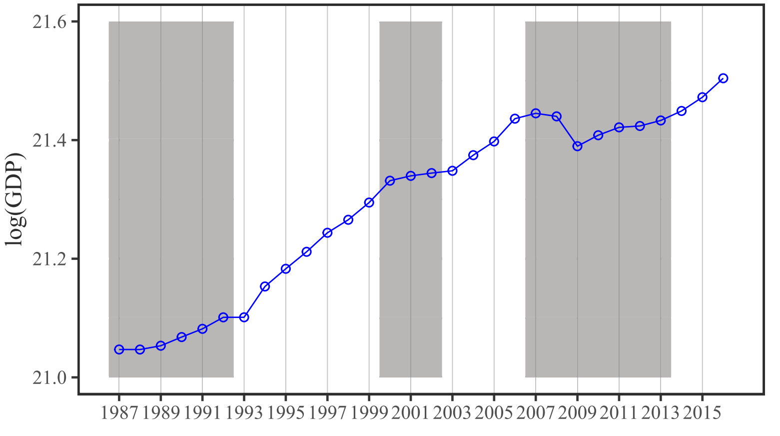

Figure 26. log GDP 1987–2016. *Notes*: The figure shows log GDP where GDP is deflated using the consumer price index, 2018 prices. The shaded areas indicate recessionary periods where GDP growth is smaller than 2%.

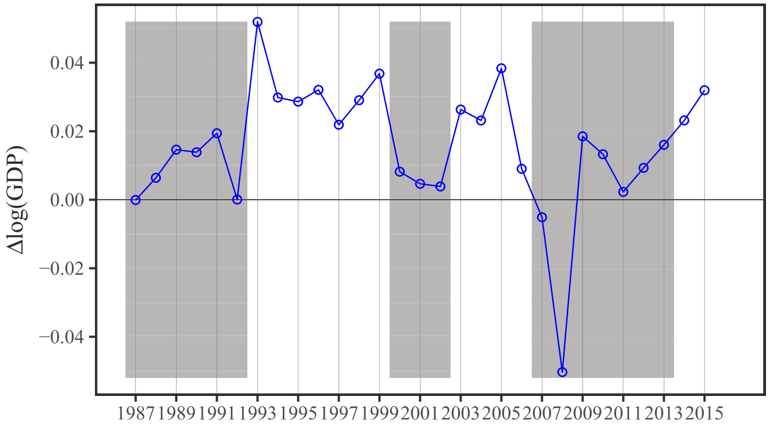

Figure 27. Annual change in log GDP 1987–2016. *Notes*: The figure shows annual change in log GDP where GDP is deflated using the consumer price index, 2018 prices. The shaded areas indicate recessionary periods where GDP growth is smaller than 2%.

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