ONLINE APPENDIX -- NOT FOR PUBLICATION

Growing Income Inequality in the United States and other Advanced Economies

By Florian Hoffmann, David S. Lee, and Thomas Lemieux

APPENDIX A: DATA APPENDIX

This appendix provides more detail on the data files used for each country, and on the challenges of obtaining comparable data over time and space.

A1. MARCH CPS DATA

As mentioned in the text, our analysis of the trends in income dispersion in the United States are based on the IPUMS files of the March Supplement (ASEC) of the CPS for 1976 to 2019, which collects income information for the preceding year (1975 to 2018). Our focus is on market income. The CPS contains information on net self-employment and wage and salary income over the reference year. We define labor income as the sum of these two income sources. In the case of capital income, we combine income from three variables in the ASEC CPS: *i)* interest income; *ii)* dividends; *iii)* rents, royalties, and income from estates or trusts.

Treatment of topcoded observations

For confidentiality reasons, the Census Bureau doesn't report actual incomes above a set threshold known as the top code. Until 1995, incomes above the top code were simply replaced by the value of the top code. For earnings items (wage and salaries or net self employment income), the top codes were $50,000 in 1976-81, $75,000 in 1982-84, and $99,999 in 1985-96, respectively. Note that, prior to 1988, the Census Bureau asked only for total earnings over the prior calendar year. Starting in 1988, separate questions were introduced for earnings on the main job held in the previous year and other jobs, when applicable. As both variables were top coded at $99,999 from 1988 to 1996, the top code for total earnings could go as high as $199,998 during this period.

The top coding procedure was improved in the 1996-2010 period by assigning a "replacement value" based on the average income of top-coded observations. Another major change implemented in the 1990s was the introduction of a computer based questionnaire. An important feature of the computer-based questions is that it enables the Census Bureau to collect much higher values of income that used to be constrained by limitations of the paper questionnaire. For instance, the highest collected value of earnings on the main job jumps from $299,999 in 1995 to $999,999 in 1996 and $1,099,999 in 1997-2019. Collecting earnings information up to $999,999 or $1,099,999 was essential for computing accurate averages among top-coded observations, as only very few individuals have earnings exceeding these high thresholds.

After 2010, the Census Bureau moved to a "rank proximity swapping" procedure where high income observations within a given range (above the top code) are swapped with close-by values and rounded off. In both cases, the top coding replacement values were applied separately to the main job and other jobs. Relative to earlier methods, the rank proximity swapping preserves the distribution above the top code, and provides more accurate measures of the income distribution. The Census Bureau has provided the swap values for years prior to 2011 that we use to keep income data consistent over time.

We find that the swap values provided by the Census Bureau for 1994-2010 do an excellent job reconstructing the upper tail of the distribution in a way that is comparable to the 2011-2019 period. Unfortunately, this is not the case prior to 1994 as swap values are constructed based on information where the "hard" top code (the highest value recorded on paper questionnaires) is much lower, as discussed above. As a result, there is a large jump in earnings at the very top between 1993 and 1994 even after correcting earnings for the 1976-1995 period using the Census Bureau swap values.

In light of this problem, we maintain consistency over time by trimming (winsorizing) the upper 1 percent on the earnings observations. Once the upper part of the distribution is removed, we no longer see a sharp jump in top incomes between 1993 and 1994. Note that we also trim capital income using the same upper cutoff point used for earnings.

Adjusting capital income

As mentioned in the text, there is mounting evidence that income items besides earnings can be severely under reported in survey data (Meyer et al., 2015). Rothbaum (2015a) shows that only about 50% of capital income as measured in the National Income and Product Accounts (NIPA) gets reported in the CPS. By contrast, close to 100% of NIPA wage and salary earnings are correctly reported in the CPS. Given the large under reporting of capital income, we adjust up reported capital income to match the NIPA figures. The adjustment factors we use are the inverse of under reporting ratios reported in Rothbaum (2015a) for 2007-12: 1/.675 for interest income, 1/.695 for dividends, and 1/.274 for rents, royalties, and income from estates or trusts.

The procedure substantially increases capital income, especially in the case of rents, royalties, and income from estates or trusts. That said, it doesn't change the main qualitative finding that capital income has been playing an increasing role in enhancing labor income inequality over time. This is illustrated in Appendix Figure A4 which reproduces Figure 1 when unadjusted capital income is used instead. Using the unadjusted data reduces the gap between labor and total income, but the overall trends remain similar.

In an effort to reduce the underreporting of capital income (and other income items besides earnings), the Census Bureau redesigned the ASEC questionnaire in 2014 by adding additional questions to help respondents report all sources of capital. In the case of interest and dividend income, proceeds inside and outside of retirement accounts should included, but this information was not always clear to respondents. One goal of the redesign was to clarify the issue to improve reporting.

Rothbaum (2015b) finds that the ASEC redesign had a large impact on interest income, increasing the amounts reported by close to 50 percent. More surprisingly, the redesign reduced the reporting of dividend income by 17 percent (the redesign did not affect questions about rental income).

As a robustness check, we recomputed capital income using the strong assumption that the redesign had eliminated all the underreporting of interest income. This further correction was implemented by not adjusting interest income with the 1/.675 factor discussed above in the (income) years 2013 to 2018. Using this alternative approach reduces the effect of capital income on the standard deviation of total income by about 0.005. This reduces the contribution of capital income to the increase in total wage inequality documented in Figure 1, but doesn't change the qualitative findings.

Summary statistics and comparison to tax data

Table A1 presents a few summary statistics from the 1975-2018 CPS data pooled over all years. Note that, unlike in the tables and figures discussed in the paper, with don't trim the top 1 percent of observations as we want to compare top income shares to those that have been reported in studies based on tax data.

Panel A indicates that most (78 percent) individuals age 25-64 received some labor income during the reference year, and that over 50 percent of individuals worked FTFY. Not surprisingly, there is a large gap in the fraction of men and women working FTFY, though the gap has been substantially shrinking over time. Panel A indicates that most (78 percent) individuals age 25-64 received some labor income during the reference year, and that over 50 percent of individuals worked FTFY. Not surprisingly, there is a large gap in the fraction of men and women working FTFY, though the gap has been substantially shrinking over time. This is illustrated in Table A2 that presents a few summary statistics from the 1975-2018 CPS data pooled over all years.

A little more than a half of individuals have some positive capital income which accounts, on average, for less than 10 percent of labor and capital income combined. For example, for men and women combined, average capital income is $3,836 compared to $41,782 for labor income. This represents 8.4 percent of labor and capital income combined. We refer to the sum of labor and capital income as total income from hereinafter.

Naturally, average earnings for FTFY workers reported in Panel B are substantially higher than average earnings for all individuals. By contrast, average capital income (and the fraction of individuals with positive capital income) is quite similar for all individuals and FTFY workers only. As a result, capital income represents a relative smaller fraction of total income for FTFY workers.

Consistent with research based on tax data (e.g. Piketty et al., 2018), Panel C shows that capital income is much more unequally distributed than labor income. For men and women combined, 37 percent of labor income goes to the top 10 percent of earners. In the case of capital income, close to 90 percent of income is concentrated among the top 10 percent. Income concentration for the top 1 percent is even more dramatic, with 10 percent of labor income and 43 percent of capital income going to this small group at the top. These figures are relatively similar to those obtained using tax data, suggesting that the March CPS does an accurate job capturing the main features of the distribution of labor and capital income once the adjustments discussed above have been performed.

Precise comparisons are challenging since tax data are reported at the household level, and are generally limited to tax filers. Nonetheless, Saez and Zucman (2016) show that about 90 percent of wealth (or capital income) is held by the top 10 percent, and around 50 percent by the top 1 percent. These figures are quite similar to those reported in Table A1. Likewise, updated figures for Piketty and Saez (2003) indicate that the share of wage and salaries going to the top 1 and 10 percent in 1975-2011 were 9 and 32 percent, respectively (the updated information is available at https://eml.berkeley.edu/~saez/TabFig2018.xls). As figures at the household level are mostly driven by the distribution of male earnings (at least in earlier years), they may be most comparable to the income shares for men reported in column 1 of Table A1. The CPS earning shares for the top 1 and 10 percent are 9 and 34 percent, respectively, which is very similar to the shares based on tax data. This suggests that the Census Bureau's rank proximity swapping procedure approximates well the upper tail of the earnings distribution.

Detailed list of occupation, industries, and MSA coding

As mentioned in the text, occupations are coded up using the same nine categories considered by Autor (2019). These categories are: *i)* health and personal services, *ii)* clean and protect services, *iii)* operators and laborers, *iv)* production workers, *v)* office and administrative occupations, *vi)* sales occupations, *vii)* technicians, *viii)* professionals, and *ix)* managers.

In the case of industries, we classify workers into 12 broad categories based on the 1990 Standard Industrial Classification (SIC) harmonized over time by IPUMS. The categories are: *i)* primary industries (including agriculture), *ii)* construction, *iii)* manufacturing, *iv)* transportation, communication, and utilities, *v)* wholesale trade, *vi)* retail trade, *vii)* finance, insurance, and real estate, *viii)* business and repair services, *ix)* personal services, *x)* entertainment and recreation services, *xi)* professional and related services, and *xii)* public administration.

Regarding the spatial distribution of workers, we use a simple classification based on whether individuals live in *i)* the 15 most populous Metropolitan Statistical Areas (MSA), *ii)* other MSAs, or *iii)* non-urban areas outside of MSAs. The 15 most populous MSAs over most of the sample period are New York City, Los Angeles, Chicago, Dallas, Washington DC, Detroit, Houston, the Bay Area, Philadelphia, Boston, Atlanta, Miami, Phoenix and Seattle.

A2. DATA FOR GERMANY

A Brief Overview of Income Data in Germany

Germany presents a challenging case for the analysis of income inequality due to a lack of data that record information on both various sources of income and a comprehensive list of demographic- and socio-economic variables. This is a result of a relatively long history of strict data protection laws,[1] with a German Supreme Court Decision in 1983 ("Volkszaehlungsurteil") being the turning point in regulating accessibility of micro data in and outside of Germany.[2] A consequence that is directly relevant for our work is that the German Mikrozensus , which is the

[1] The first data protection act in the world was enacted in the German state of Hesse in 1970.
[2] Some implications are: (a) Micro-data collected by public institutions, such as the German Statistical Office or the German Employment Agency can only be accessed physically at selected data research centers, which are, in the case of the former, all located in Germany; (b) The Luxembourg Income Study changed from using the German Income and Consumer Survey (EVS), which is administered by the German Statistical Agency, in and before 1983 to using the German Socioeconomic Panel (GSOEP); (c) Germany only submits a subset of variables to the European Labor Force Survey, a data project that attempts harmonizing administrative data collection across EU membership states.

data set coming closest to the US Current Population Survey (CPS), only contains rudimentary information about individual income. Early studies of trends in German income inequality, such as Steiner and Wagner (1998), therefore tend to rely on the German Socio-economic Panel (GSOEP) survey data. However, findings in Dustmann, Schoenberg and Ludsteck (2009) that are based on administrative labor market data from the social security administration suggest that the GSOEP income data tend to understate trends towards higher income inequality in Germany since the 1980s. Subsequent studies that rely on social security data, such as Card, Kline and Heining (2013) and Hoffmann (2019), corroborate the findings of a steady increase in German labor income inequality over the last three decades.

Unfortunately, for the purpose of this study, the social security data are not well suited, for two reasons. First, they only report wage- and salaried income from dependent labor, thereby excluding income from capital and self-employment. Second, they are top-coded at the social security upper contribution limit, and this top-code is approximately at the 90th percentile of the labor income distribution. Moreover, it affects over-proportionally the earnings of the highly educated, thereby making estimation of returns to education difficult.[3] This strict top-coding, which is inherent in how the social security data are collected, explains the paucity of empirical evidence on trends in German top-level income inequality. An exception is Bartels (2017), which estimates the share of total income going to high earners for 1871 to 2013 using Pareto-imputation on tables from the official German income tax statistics.[4] One contribution of our paper is to provide some recent evidence on the evolution of income inequality using data that report high incomes from dependent labor and self-employment and from capital.

Data

Our study relies on data from the German Income and Consumer Survey (EVS: Einkommens- und Verbrauchsstichprobe) provided by the Federal Statistical Office of Germany (Statistisches

[3] Card, Kline and Heining (2013) report that approximately 12 percent of all observations on income in their data is top-coded. Hoffmann (2019), in a study of life-cycle income inequality, finds that among the prime-aged highly educated, the share of top-coded observations can be as high as 55 percent.
[4] Bartels and Jenderny (2015) confirm using confidential micro-level tax data that the Pareto-imputation procedure on the official tax tables provides an accurate picture of recent trends in top-level income inequality in Germany. These data do not report educational attainment however and can therefore not be used for our study.

Bundesamt) for the years 1983 to 2013. The EVS is a cross-sectional data set on the household level that is collected in five year intervals by the federal- and state-offices of the German Statistical Office. Each wave of the data contains approximately 60,000 households, which are asked to record their income and their expenditure for a period of 3 months. They serve for determining the consumption basked for the calculation of the official consumer price index and for calculating the income thresholds of unemployment- and social insurance. The Federal Statistical Office explicitly highlights its high accuracy. However, there is some evidence that it is affected by underreporting of income from self-employment and income from wealth, an issue that needs to be kept in mind in interpreting the result below. Furthermore, households above a certain income threshold are not included in the data. While this threshold is high and well above the 99th quantile of the income distribution in most year, it does truncate our earnings data, and the truncation point changes over time. We describe below how we address this issue.

To produce a sample that is closely comparable to our U.S. data from the CPS, we apply similar sample restrictions. To this end we need to discard the EVS samples from before 1998 since they have only partial information on person- rather than household-level income. They also do not provide a full-time work indicator. Fortunately, starting in 1998 we can compute personal income variables that are closely comparable to those in the CPS. In particular, labor income is the sum of income from employment, including one-time payments such as bonuses and premiums, and from self-employment. Capital income is the sum of income from interest, dividends and rents. In contrast to labor income, in all waves of the EVS this variable is available on the household level only. As for the other European countries in our analysis we assume that it is shared equally across household members.

Addressing Truncation

For confidentiality reasons, the EVS data are affected by truncation: Households with total income above a certain threshold are excluded from the sample. The truncation thresholds are generally quite high, but they have become smaller in real terms over time. More specifically, the threshold was 35,000 DM in1998 and 18,000 EUR afterwards. With a conversion rate of approximately 2:1, the threshold has thus remained effectively constant in ***nominal*** terms. If not properly corrected for, any trends in top-level inequality will thus be understated, as the share of high-income households included in the data is decreasing over time. We combine two sets of external information to address this problem. First, we take advantage of the weights provided by the Statistical Office, which are taken from the Mikrozensus. These weights are constructed so that each household can be interpreted as a random draw from the full distribution of households, not the distribution of households below the income threshold. Second, we use the tables from the official German income tax statistics and follow the methodology in Bartels (2017) for constructing percentiles of the personal earnings distribution. Fortunately, the definition of income in these tables and the definition of income we use in our analysis, i.e. the sum of labor- and capital income, are identical. We then discard any individuals whose income is above the year-specific 98.5%-percentile of the earnings distribution, as computed from the official income tax statistics.[5]

A3. FRANCE, ITALY, AND THE UNITED KINGDOM

As noted in the text, the data sets for France, Italy, and the United Kingdom are obtained via the Luxembourg Income Survey (LIS) project, which harmonized version of the data files. Two important differences relative to the March CPS are that *i)* capital income only collected at the household level, and *ii)* the information on full-time status and annual weeks of work. We adjust for the first issue by simply dividing household capital income by the number of individuals age 25-64 in the household. We address the second issue by only keeping years where full-time status is available, and limiting the analysis to full-time workers earnings more than $8000 (in dollars of 2018 converted in local currency) instead of only keeping full-time/full-year workers.

[5] We choose the 98.5%-percentile instead of the 99%-percentile since the highest income in the 2013 EVS is very close to this percentile. In terms of 1995 EUR, the values of these thresholds are 106,225 EUR in 1993, 102,340 EUR in 1998, 99,026 in 2003, 114,021 in 2008 and 125,011 in 2013.

APPENDIX B: CHANGES IN UPPER TAIL INEQUALITY IN GERMANY

One main advantage of relying on the EVS instead of the administrative social security data used in Dustmann, Schoenberg and Ludsteck (2009), Card, Kline and Heining (2013) and Hoffmann (2019) is that it reports high incomes. However, the EVS excludes extremely high earners. While truncation thresholds are high, and while we have used external information to address this issue, it may still bias downward trends in income inequality. It is thus worthwhile todocument trends in upper-tail inequality in Germany. To this end we plot the 10th, 50th, 90th and 99th percentiles of total income in Appendix Figure B1.[6] The picture that emerges from this is quite striking. For both women and men, median income remained almost constant for the entire period, while the 10th percentile declined. This erosion of earnings at the bottom of the distribution, even among full-time workers, has been documented in a number of papers, including Card, Kline and Heining (2013) and may therefore be taken as one of the truly robust stylized facts about earnings inequality in Germany. On the other hand, our findings about trends in top-level inequality are less well-known in the literature, mainly due to the lack of data discussed in the introduction. For men, both p90 and p99 saw only a slight increase between 1998 and 2008. Women at the top of the earnings distribution even experienced a decline in the five years between 2003 and 2008. However, after 2008 there is a sharp trend break, with top income levels starting to grow at substantially larger rates. Furthermore, this increase in upper-tail inequality becomes stronger the further we move to the right of the earnings distribution. It is thus the years after the Great Recession when the German earnings distribution opened up most dramatically.

How do these results on upper-tail inequality in Germany compare to the existing literature? Bartels (2019) offers the most complete picture of this aspect of earnings inequality using published tables from the official German income tax statistics. Her findings are entirely consistent with ours. Importantly, she finds that the p99 reached a first maximum in 1989 before **declining**

[6] Using total income instead of labor income makes comparison with existing results from tax income tables more straightforward. The trends are very similar for labor income.

steadily until 2003. With a brief interruption during the Great Recession, it has increased afterwards, with a dramatic acceleration between 2010 and 2013.[7]

To conclude, the German trend towards higher earnings inequality among full-time workers who have earnings below the 90th percentile is consistently found in various sources of data. Of particular importance is the dramatic erosion of real earnings at the bottom of the distribution. Matters are, somewhat surprisingly, different above the 90th percentile. The evidence is relatively scarce, but also consistent across the few data that are well-suited for estimating top-level inequality. In particular, inequality above the 90th percentile remained relatively stable – with a 10-year interruption during which it actually declined – between the German reunification and the Great Recession. Since then it has increased dramatically. Most importantly for the purpose of our analysis, our EVS results agree with those found from administrative tax tables.

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[7] Bartels (2019) plots income shares instead of percentiles. The percentile we mention here can be found in her table A.1. Bartels lists detailed references to the official tax tables, which are publicly available, in her table B.1.

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LIST OF APPENDIX FIGURES AND TABLES

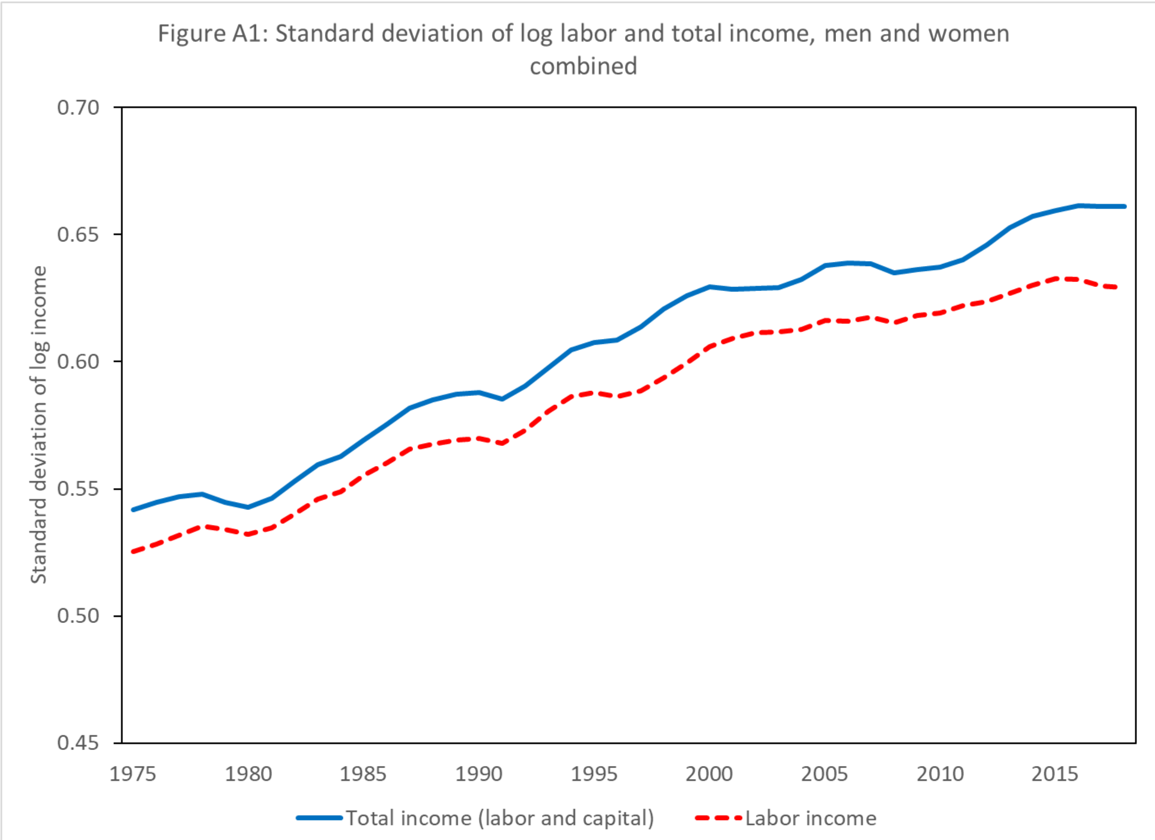
Figure A1: Standard deviation of log labor and total income, men and women combined
Standard deviation of log income
0.70
0.65
0.60
0.55
0.50
0.45
1975
1980
1985
1990
1995
2000
2005
2010
2015
Total income (labor and capital)
Labor income

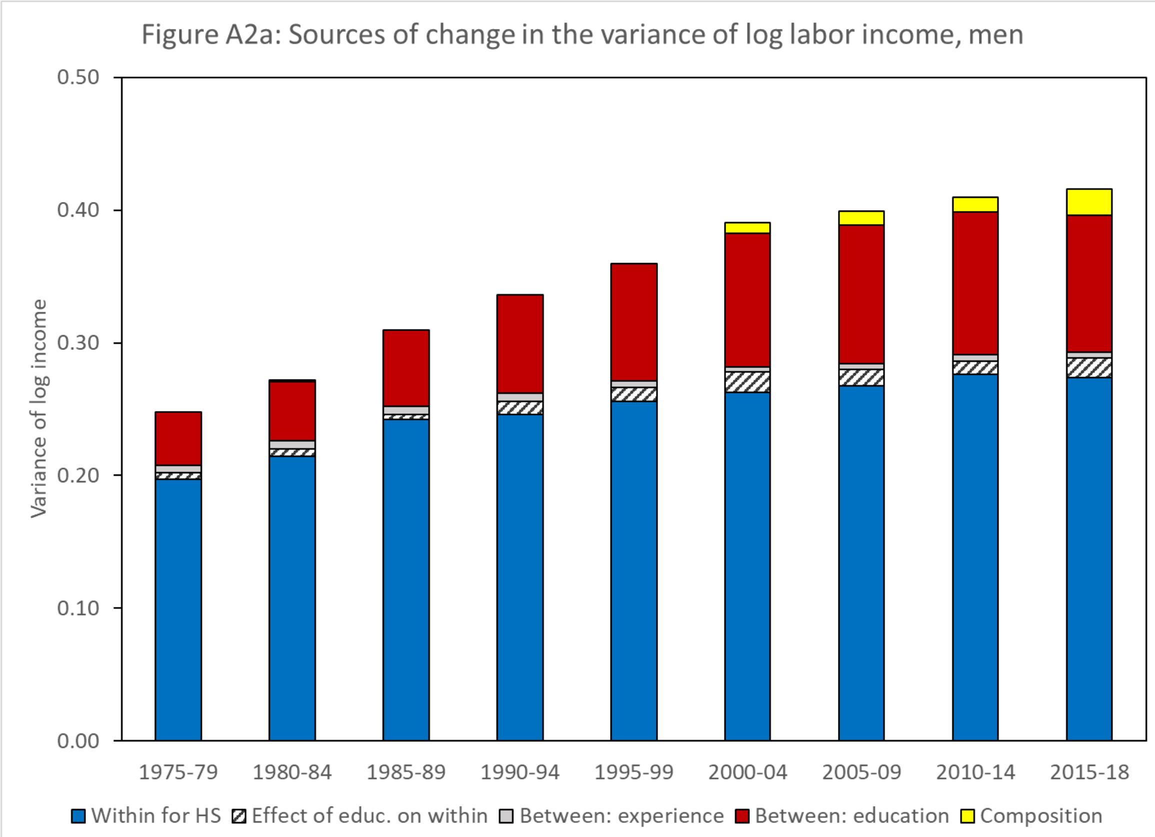
Figure A2a: Sources of change in the variance of log labor income, men
0.50
0.40
0.30
0.20
0.10
0.00
Variance of log income
1975-79
1980-84
1985-89
1990-94
1995-99
2000-04
2005-09
2010-14
2015-18
Within for HS
Effect of educ. on within
Between: experience
Between: education
Composition

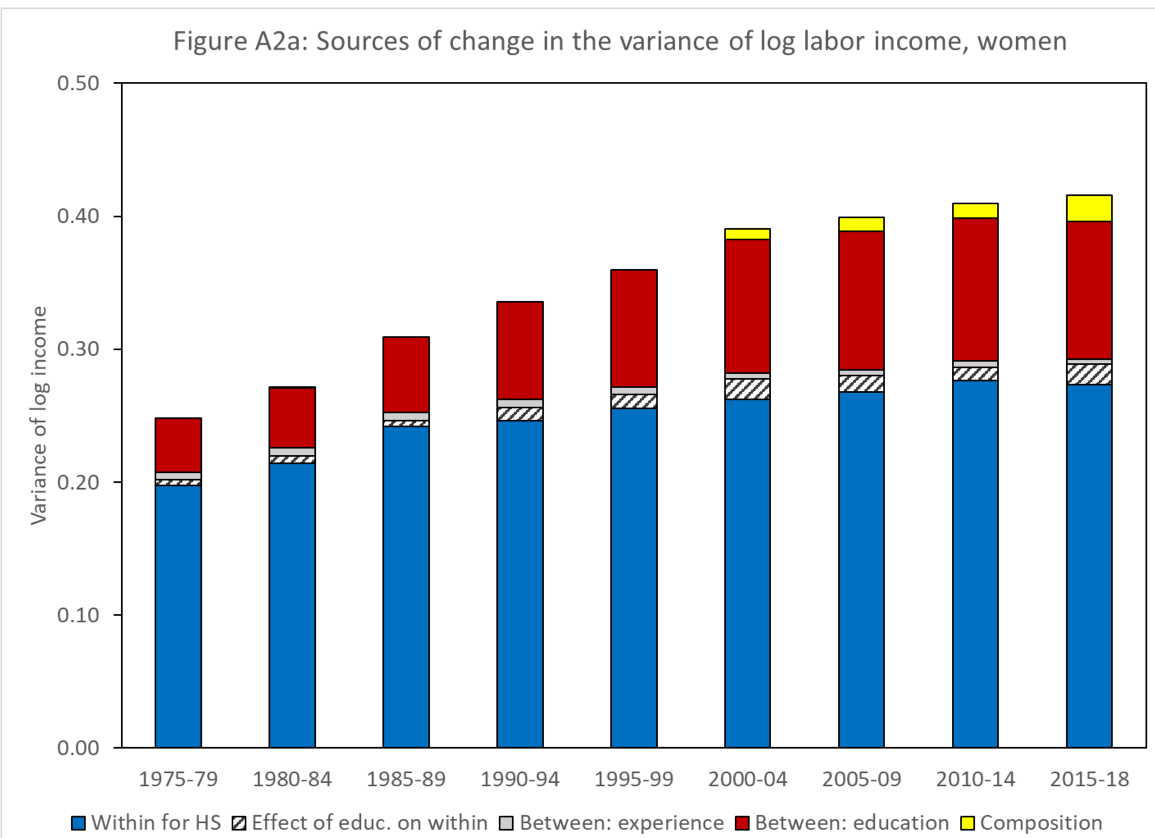
Figure A2a: Sources of change in the variance of log labor income, women
0.50
0.40
0.30
0.20
0.10
0.00
Variance of log income
1975-79
1980-84
1985-89
1990-94
1995-99
2000-04
2005-09
2010-14
2015-18
Within for HS
Effect of educ. on within
Between: experience
Between: education
Composition

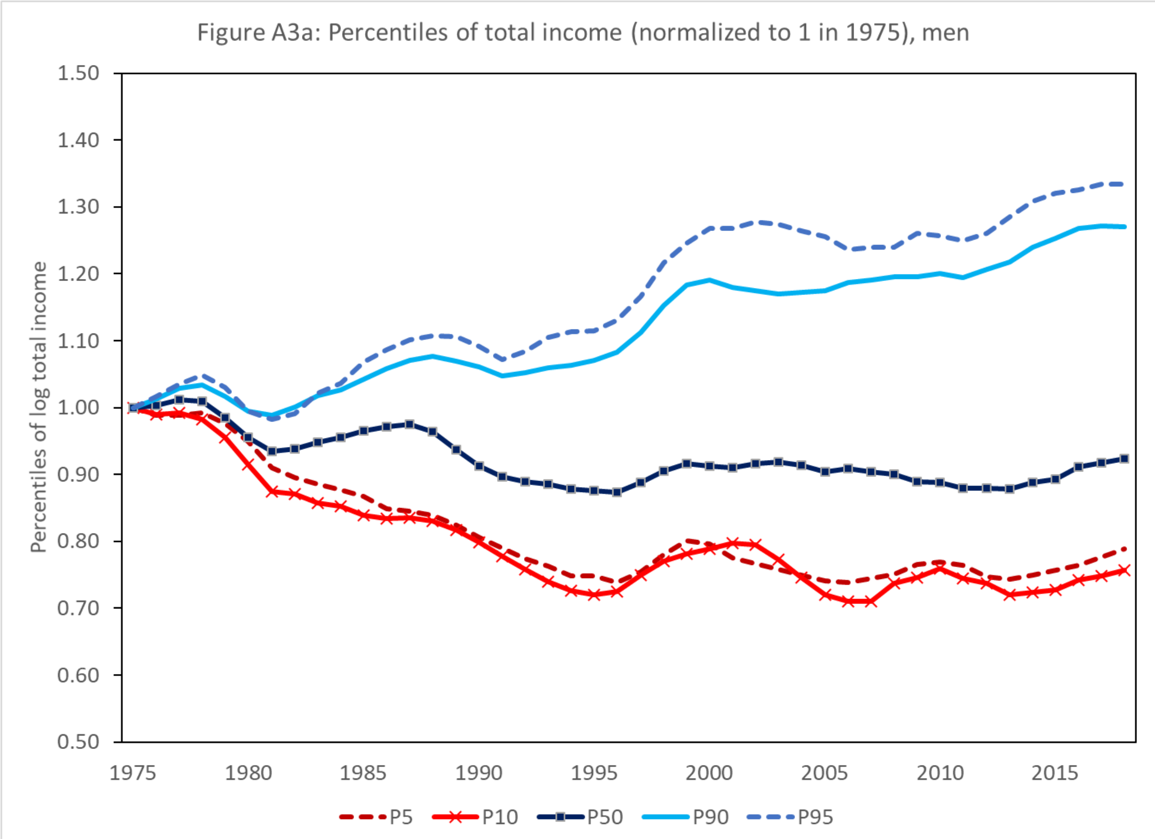
Figure A3a: Percentiles of total income (normalized to 1 in 1975), men
Percentiles of log total income
1.50
1.40
1.30
1.20
1.10
1.00
0.90
0.80
0.70
0.60
0.50
1975
1980
1985
1990
1995
2000
2005
2010
2015
P5
P10
P50
P90
P95

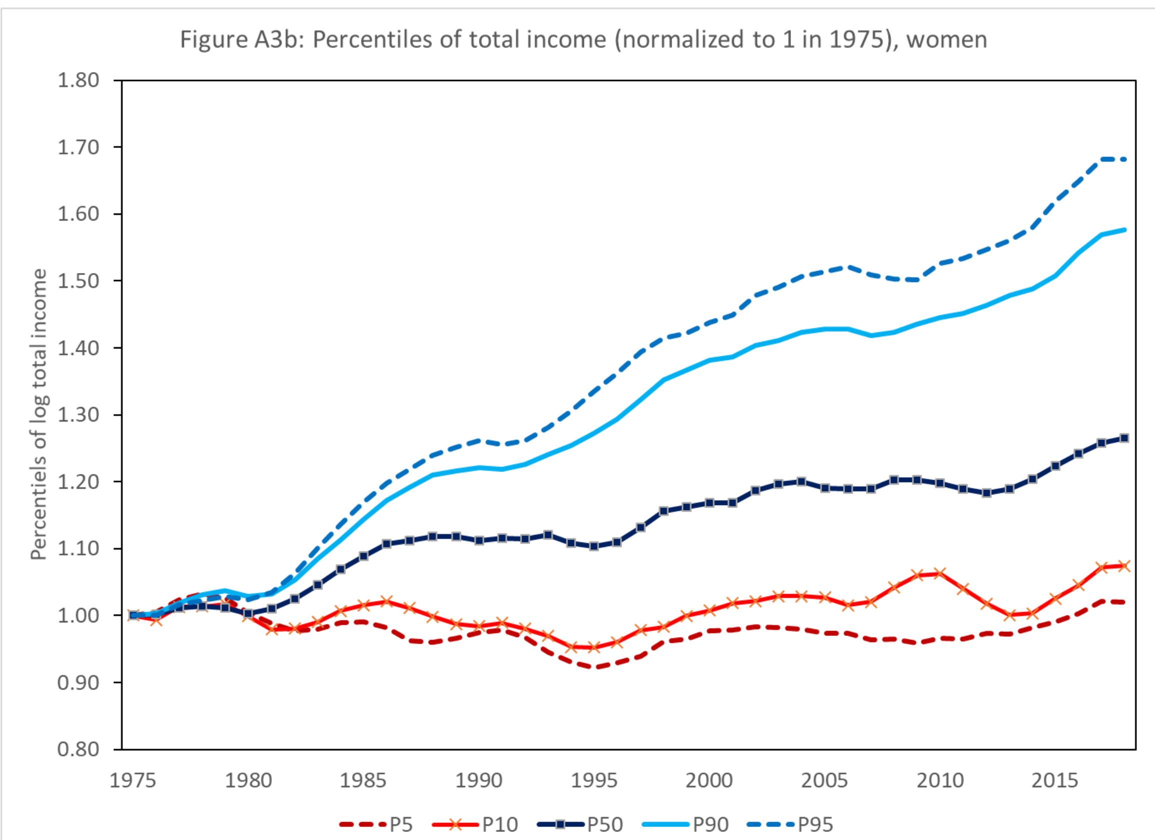
Figure A3b: Percentiles of total income (normalized to 1 in 1975), women
Percentiels of log total income
1.80
1.70
1.60
1.50
1.40
1.30
1.20
1.10
1.00
0.90
0.80
1975
1980
1985
1990
1995
2000
2005
2010
2015
P5
P10
P50
P90
P95

Figure A4a: Standard deviation of log labor and total income with unadjusted capital income, men

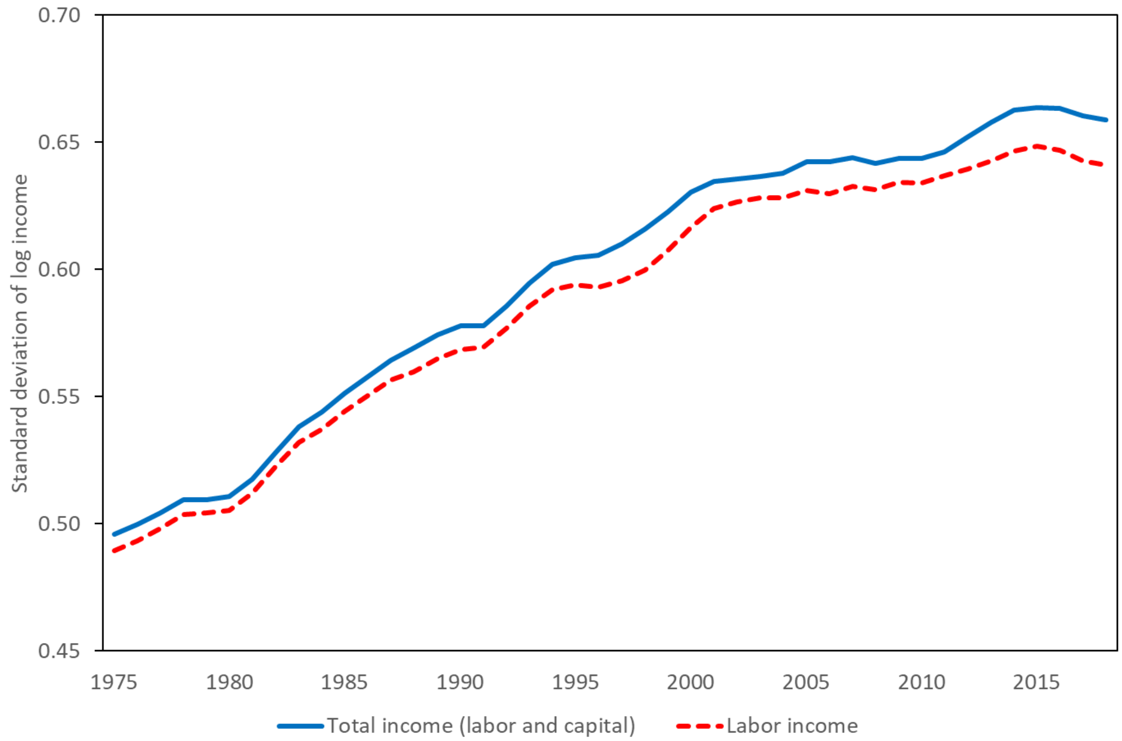

Figure A4b: Standard deviation of log labor and total income with unadjusted capital income, women

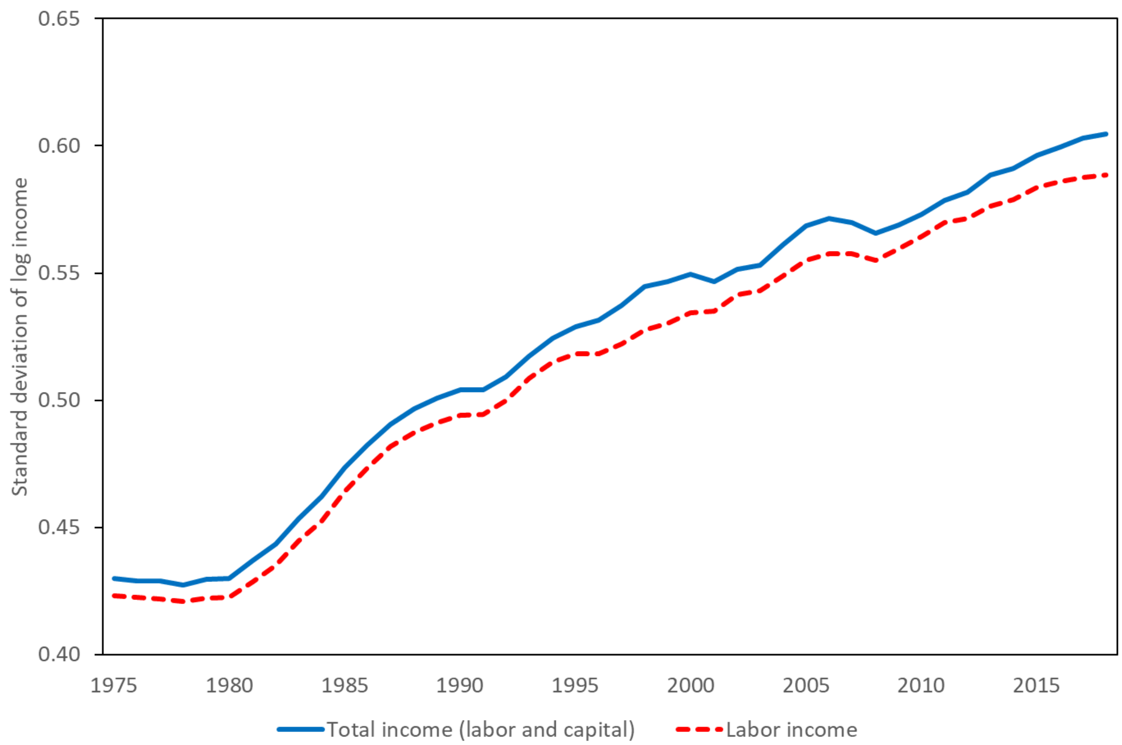

Figure B1a: Percentiles of total income (normalized to 1 in 1998) in Germany, men

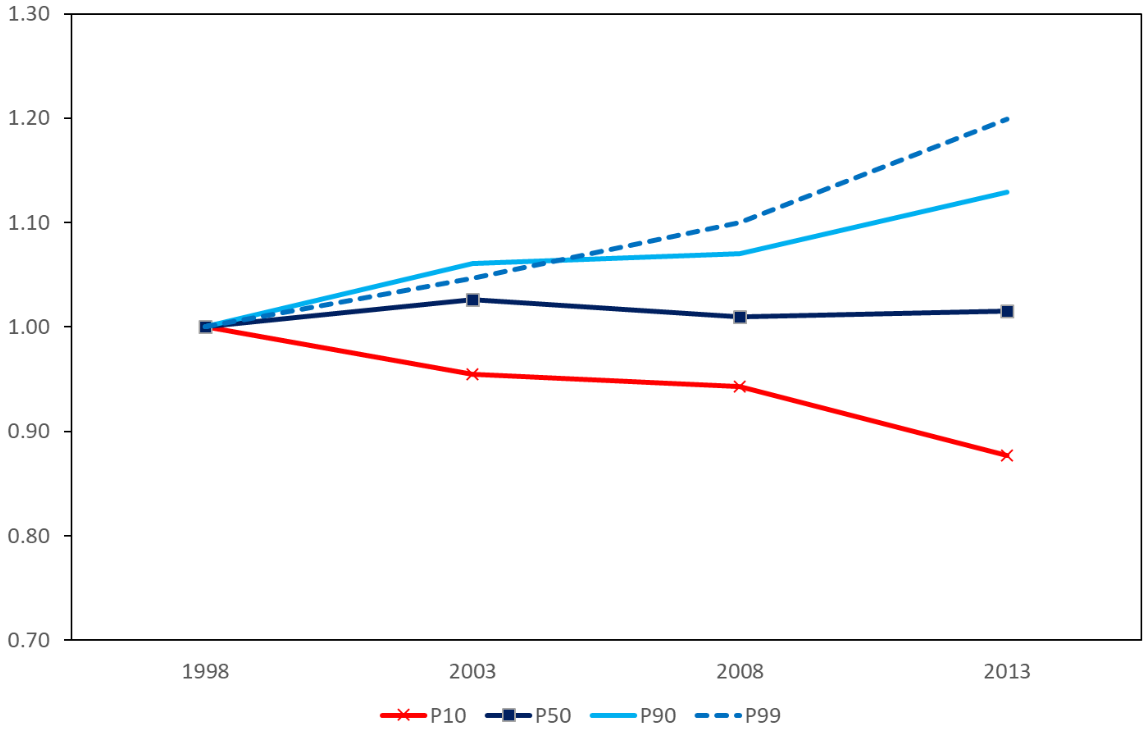

Figure B1b: Percentiles of total income (normalized to 1 in 1998) in Germany, women

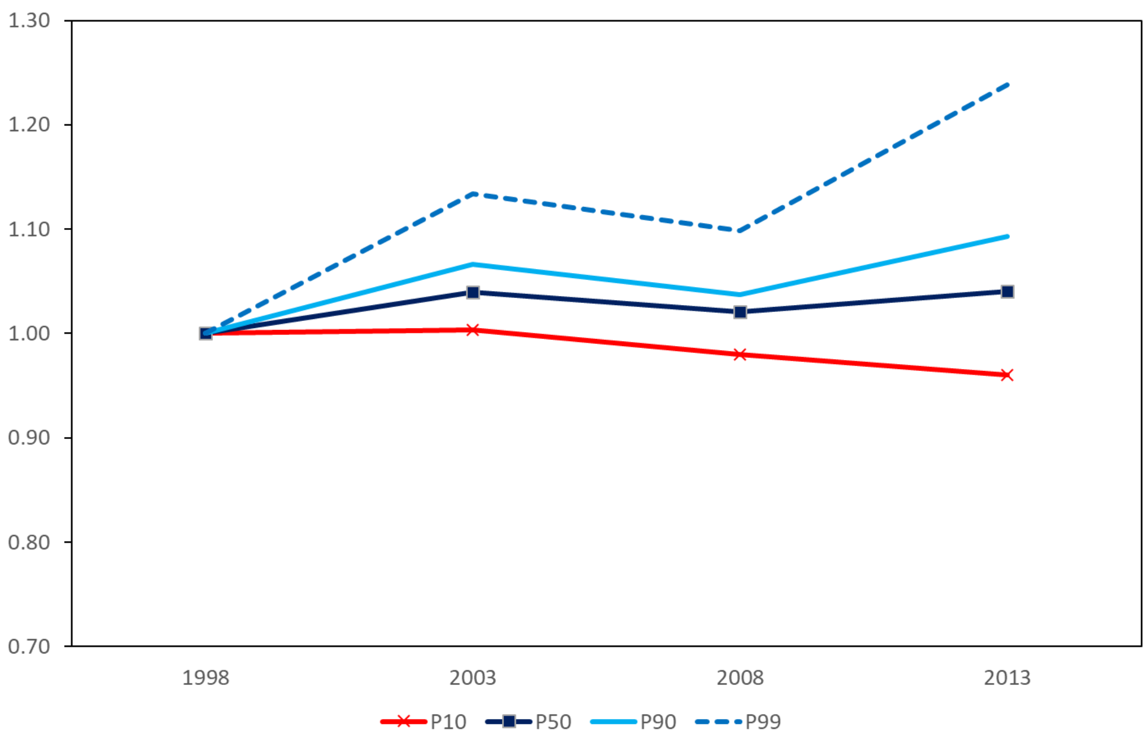

Table A1: Summary statistics on income, 1975-2018 March CPS

	Men	Women	All
A. All individuals 25-64			
Positive earnings	0.865	0.704	0.783
Full-time/full-year	0.658	0.384	0.518
Positive cap. Income	0.544	0.515	0.529
Average earnings	56,716	27,517	41,782
Average cap. income	4,321	3,372	3,836
B. Full-time/full-year			
Positive cap. Income	0.623	0.599	0.614
Average earnings	75,020	51,902	66,244
Average cap. income	4,576	3,215	4,059
C. Concentration at the top (all individuals)			
Top 10% earnings	0.338	0.368	0.367
Top 1% earnings	0.094	0.084	0.099
Top 10% cap. income	0.884	0.895	0.890
Top 1% cap. income	0.414	0.440	0.427

Table A2: Summary statistics by decade, 1975-2018 March CPS

	1975-79	1980-89	1990-99	2000-09	2010-18
A. All men age 25-64					
Positive earnings	0.906	0.887	0.881	0.859	0.830
FTFY	0.671	0.648	0.671	0.669	0.641
Positive cap. Income	0.534	0.627	0.587	0.488	0.509
Average earnings	58,061	54,119	55,674	59,343	56,525
Average cap. income	4,122	4,184	4,517	4,167	4,459
B. FTFY Men					
Positive cap. Income	0.592	0.705	0.665	0.558	0.601
Average earnings	72,735	70,974	72,533	77,996	77,803
Average cap. income	4,138	4,239	4,689	4,276	5,145
C. All women age 25-64					
Positive earnings	0.595	0.671	0.736	0.732	0.709
FTFY	0.246	0.317	0.393	0.428	0.427
Positive cap. Income	0.300	0.607	0.586	0.482	0.489
Average earnings	16,316	20,513	26,819	31,650	32,594
Average cap. income	2,141	3,907	3,838	3,380	2,984
D. FTFY Women					
Positive cap. Income	0.396	0.673	0.661	0.544	0.601
Average earnings	41,019	43,656	48,537	54,716	58,040
Average cap. income	1,878	3,146	3,468	3,171	3,335

Appendix Table A3: Comparing changes in the variance of labor and total income by country

	Men			Women		
	Total income	Labor income	Difference	Total income	Labor income	Difference
United States (adjusted capital income)						
1989	0.4204	0.3981	0.0223	0.3338	0.3169	0.0170
2018	0.4875	0.4469	0.0406	0.4059	0.3742	0.0317
Change	0.0671	0.0488	0.0183	0.0720	0.0573	0.0147
United States (unadjusted capital income)						
1989	0.4088	0.3981	0.0107	0.3242	0.3169	0.0073
2018	0.4673	0.4469	0.0204	0.3921	0.3742	0.0179
Change	0.0584	0.0488	0.0096	0.0679	0.0573	0.0106
France						
1994	0.1997	0.1945	0.0051	0.1467	0.1419	0.0048
2005	0.1872	0.1831	0.0041	0.1446	0.1389	0.0057
Change	-0.0125	-0.0115	-0.0011	-0.0021	-0.0030	0.0009
Italy						
1989	0.1050	0.0988	0.0062	0.0732	0.0657	0.0076
2016	0.2588	0.2559	0.0030	0.1806	0.1779	0.0027
Change	0.1538	0.1571	-0.0032	0.1073	0.1122	-0.0049
Germany						
1998	0.1850	0.1803	0.0047	0.1799	0.1771	0.0028
2013	0.2706	0.2701	0.0006	0.2331	0.2320	0.0011
Change	0.0857	0.0898	-0.0041	0.0533	0.0549	-0.0016
United Kingdom						
1999	0.2700	0.2691	0.0009	0.2272	0.2246	0.0026
2016	0.3511	0.3534	-0.0023	0.2702	0.2697	0.0005
Change	0.0812	0.0843	-0.0031	0.0430	0.0451	-0.0021