

Family and Government Insurance: Wage, Earnings, and Income Risks in the Netherlands and the U.S.

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Abstract

We document new facts about risk in male wages and earnings, household earnings, and pre- and post-tax income in the Netherlands and the United States. We find that, in both countries, earnings display important deviations from the typical assumptions of linearity and normality. Individual-level male wage and earnings risk is relatively high at the beginning and end of the working life, and for those in the lower and upper parts of the income distribution. Hours are the main driver of the negative skewness and, to a lesser extent, the high kurtosis of earnings changes. Even though we find no evidence of added-worker effects, the presence of spousal earnings reduces the variability of household income compared to that of male earnings. In the Netherlands, government transfers are a major source of insurance, substantially reducing the standard deviation, negative skewness, and kurtosis of income changes. In the U.S. the role of family insurance is much larger than in the Netherlands. Family and government insurance reduce, but do not eliminate nonlinearities in household disposable income by age and previous earnings in either country.

Keywords: Wage risk, self-insurance, social insurance, progressive taxation, redistribution, life cycle

JEL classification: D31, E24, J31, H31

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1 Introduction

Wage risk affects key economic decisions, including consumption, saving, and labor supply, and is an important determinant of household's welfare. Households can self-insure against wage shocks: single people can adjust their own labor supply and savings and couples can adjust the labor supply of both partners, in addition to savings. Furthermore, governments can supplement or partly replace the need for self-insurance through progressive taxes and transfers.

This paper studies the distribution of wage shocks and the role of insurance mechanisms against them in the Netherlands and the United States. We start by documenting the distribution of wage shocks at the individual level by analyzing distributional measures of wage changes, including the standard deviation, skewness, kurtosis, and persistence, by age and previous earnings. To understand the role of individual-level labor supply and fluctuations in hours, we compare the distribution of individual wage shocks with that of individual-level earnings. To analyze the role of family insurance through the labor supply of both partners, we compare the distributions of individual-level and household-level earnings. To examine the role of government insurance, we compare the distribution of household income, pre- and post-taxes, and transfers, by age group and previous earnings.

We use administrative data on income, taxes, and government transfers on individuals and households for the Netherlands (IPO) to get precise estimates of the dynamics of wage shocks and the role of private and public insurance mechanism to mitigate these shocks. We compare the results with estimates for the U.S. Panel Study of Income Dynamics (PSID), and find that the distribution of wage and earnings shocks display rich dynamics and, particularly, depend on age and previous earnings in both countries, as was previously documented for earnings in the U.S. (Guisar, Karahan, Ozkan and Song, 2015, and Arellano, Blundell and Bonhomme, 2017).

Our contribution to the literature is threefold. First, whereas most previous studies investigated shocks to individual earnings, we distinguish between changes in wages and changes in hours worked. As the two may have different dynamics, this provides us with a better understanding of the nature of income risk. Using high-quality Dutch administrative data on hours worked derived from payroll administration, we find that hours are the main driver of the variability at the bottom of the earnings distribution, the

negative skewness and, to a lesser extent, the high kurtosis of earnings. This differs from what we find in Dutch household survey data (DNB Household Survey) or the PSID, and suggests that accurate measurement of earnings and hours worked is crucial to properly account for wage dynamics.

Second, we investigate the degree of insurance provided by spousal labor supply and by the tax and transfer system. We find that the family is a relevant source of insurance in the Netherlands, but most of this insurance comes from income pooling rather than labor supply reactions of secondary earners or added worker effects. Taxes and, particularly, the transfer system play an even larger role in reducing income risk.

Third, we compare two countries: the Netherlands and the U.S. This is an interesting comparison because these two countries differ substantially in the size of their welfare state and the progressiveness of their tax system.¹ We find that family insurance is more relevant in the U.S. than in the Netherlands, whilst in the latter the government is responsible for the bulk of the reduction in income risk. This also holds if we compare survey data across both countries. Finally, our analysis provides data that rich models of risks and insurance should match to be consistent with the key features of the micro-data that we document.

Our paper contributes to a growing literature on higher-order moments of income shocks. Guvenen et al. (2015) investigate higher order earnings risk using US Social Security administrative data. They find substantial nonlinearities and non-normalities, but they can only study gross individual earnings process, so they cannot separate hours and wages or study additional insurance mechanisms. Hoffman and Malacrino (2019) use Italian administrative data to decompose earnings growth in changes in employment time and changes in weekly earnings. Like us, they find that changes in employment time are the main driver of earnings growth. Halvorsen, Holter, Ozkan and Storesletten (2019) analyze Norwegian data and attribute changes in earnings mostly to changes in wages. These international differences suggest that country-specific institutional features are important to determine whether wages or hours are the most important margin of

¹Although eligibility requirements have become more restrictive over the past two decades, the Dutch welfare system is one of the most comprehensive in Europe; see Kalwij, Kapteyn and de Vos (2018) for a detailed and up-to-date description of social security reforms in the Netherlands. The OECD Social Expenditure Database 2016 shows that public social expenditure on family support, disability, unemployment and active labor market policies as a percentage of GDP is twice as high in the Netherlands compared with the U.S.

adjustment. Similarly to our results, Halvorsen et al. (2019) find that the benefit system is particularly important to insure workers against earnings fluctuations. Pruitt and Turner (2018), use administrative data from the U.S. and find that the probability of the secondary earner entering employment rises when the primary earner experiences earnings losses.

There is mounting interest in the higher-order moments of income shocks. They are key input for models on asset prices (Mankiw, 1986; Constantinides and Ghosh, 2017; Schmidt, 2016), monetary policy (Kaplan, Moll and Violante, 2018), and optimal social insurance and taxation (Golosov, Troshkin and Tsyvinski, 2016). Taking into account higher-order moments also influence estimates on the welfare costs of earnings fluctuations (De Nardi, Fella and Paz-Pardo (2019) find that they are smaller when taking into account higher-order moments).

These rich features derive from important economic mechanisms (Postel-Vinay and Turon (2010) and Graber and Lise (2015)). For instance, a job ladder model can explain negative skewness and some kurtosis because most people stay on the job and experience small wage raises, while a small number of people lose their job and face large wage and earnings drops. In addition, the persistence of these wage changes might depend on one's age (a young worker is more likely to experiment and switch jobs to figure out what he or she is best at) while an old worker might switch to a part-time or less demanding job.

The remainder of the paper proceeds as follows. Section 2 describes our data and approach, Sections 3 and 4 present the results and Section 5 concludes.

2 Data and empirical approach

This section provides an overview of the data we employ, the sample selection criteria, the variables used in our empirical analysis, and our empirical approach.

2.1 The data

The Dutch data We use two data sets for our main analysis: (1) administrative tax records from the Dutch Income Panel Study (IPO) which contain detailed information of various income sources and (2) administrative data on hours worked from the Dutch payroll administrations (DPA). The IPO data set contains detailed information on, amongst

others, personal income, household income, demographics, and labor market status for a representative 1% population sample (about 95,000 individuals) and their household members. While the data is available since 1989, we use it starting in 2001, due to a change in the income definition in that year, and until 2014.

The IPO data set has several important advantages over survey data. First, the data is often collected or checked by a third party. For instance, income measures are derived from tax records complemented with information provided by banks and other financial institutions. In addition, Statistics Netherlands performs several checks on the data to guarantee their quality. This drastically reduces or even eliminates measurement error and errors due to non-reporting. Second, individuals are in the panel from the year of birth (for immigrants, the year of arrival) and are followed for as long as they are residing in the Netherlands (as of December 31 of the sample year). Thus, attrition only occurs as a result of migration or death. Third and very importantly, unlike other administrative data sets such as the US Social Security Administration's, the IPO data set tracks households rather than only individuals and contains a detailed decomposition of labor and asset income, taxes and social insurance premia paid, as well as government transfers (broken down into unemployment insurance, disability insurance, social assistance, and pensions) received for all household members. This feature crucially allows us to investigate the role of both the family and government insurance in reducing income fluctuations.

The DPA payroll data provides very rich information on the number of days and hours worked. It is obtained directly from employers. Dutch legislation mandates that all employers maintain up-to-date payroll records and report them to the relevant government agencies on a monthly basis. The payroll records include information on (a) the start and end date of the employment spell, (b) earnings, (c) the number of regular hours and (d) the number of overtime hours that each employee has worked in a given month. These data are not only salient for processing and paying salaries, but also for the computation of holiday entitlement, social insurance benefit payments, and pensions (see Appendix A for an extensive documentation on this).

From 2006 onwards, we have access to the complete payroll records for each employee, and thus have as accurate information on hours as possible. For the period before 2006, Statistics Netherlands provides researchers with a summary measure of hours that has two limitations: (a) it is normalized by "typical" working hours in a sector and (b) it

is capped at fulltime hours. We address the first limitation of the pre-2006 data by computing the typical workweek in each sector in the post-2006 data and using it to re-normalize the data for each sector in the pre-2006 data. Concerning the cap at full-time hours, it constrains the measurement of overtime hours for full-time workers, but not for part-time workers, as long as the total number of hours worked does not exceed full time hours.²

The U.S. data For the U.S., we use data from the Panel Study of Income Dynamics (PSID).³ This data set began in 1968 with a representative sample of 18,000 individuals living in 5,000 households. We use it for the period 1968 to 1992. We exclude the years 1993-1997, because of a major redesign of the survey, and those after 1997 because the PSID became bi-yearly after that date. To confirm that our results are not driven by the different sample periods between the U.S. and the Netherlands (see Heathcote, Perri and Violante, 2010 for a discussion of changes in the distribution of wages and earnings in the U.S. across this period of time), in Appendix D.1 we compare our statistics of interest for the period after 1997 for two-years income changes in both countries. This robustness check shows that the cross-country differences that we document are driven by country-specific differences rather than different sample periods.

2.2 Empirical approach

To investigate the role of various insurance mechanisms, we conduct our analysis on male wages and earnings, household earnings, and household after-tax (disposable) income. Comparing individual wages and earnings is informative about self-insurance through labor supply, while comparing individual- and household-level earnings conveys information about family insurance through the labor supply of the spouse. Finally, comparing household pre- and post-tax income sheds light on the role of government-provided insurance through transfers and progressive taxation.

To capture, in line with recent contributions (Guvenen et al., 2015; Arellano et al., 2017; De Nardi et al., 2019), richer patterns of risks than typically assumed in the previous

²To evaluate the effects of missing overtime hours for full-time workers before 2006, Appendix B compares our results for our complete sample period with those we obtain using only the post-2006 sample period. The results are extremely close.

³Appendix C documents our findings using survey data for the Netherlands.

literature, we follow Guvenen et al., 2015 and report key moments of the distribution of the (one-year) changes of the log of each variable of interest by age group and percentile of the distribution of male earnings in the previous year.⁴

To be consistent with the related literature on rich earnings risk, we follow similar sample selection, variable definition, purging of age and time effects, and moment computation. In terms of sample selection, for each country we select working-age male earners with some labor market attachment and who are not self-employed. More specifically, for an individual-year observation to be in our sample, the individual (a) must be between 25 and 60 years old, (b) have annual labor earnings above a minimal threshold (2,200 euro in 2014 prices, which is around 4% of median earnings), and (c) not receive self-employment income as a main income source. Appendix D.6 reports results when we do not impose this minimal earnings threshold and we compute arc-percentage changes instead of changes in logs. The results show that government insurance is stronger when we consider zeros.

In terms of variables definition, we define individual gross earnings as the total remuneration received by an employee in a given year, which includes his contributions to social security.⁵ We compute household gross earnings by aggregating individual earnings of all household members.⁶ By adding income from savings, we obtain household pre-tax income. Finally, household after-tax income equals household pre-tax income minus income taxes (including allowances, such as healthcare, rent, child and child care, study costs, and alimony), plus transfers. Transfers are the sum of unemployment benefits, disability benefits, social assistance, and pension benefits. Finally, wages are computed by dividing yearly labor earnings by hours worked within the year.

To purge age and time effects from yearly changes and from the distribution of previous earnings, we take residuals from a regression on a (quadratic) polynomial in age and time dummies.

The moments that we consider include second and higher-order moments and quantile-based measures.⁷ Our quantile-based measures of skewness and kurtosis are Kelley's

⁴Appendix D.2 also reports those conditioning on earnings over the past 5 years rather than past year.

⁵In the Netherlands, employee's contributions to social security include a contribution for health insurance and a premium for unemployment, disability, and pension benefits.

⁶We equalize all of our earnings measures using the equivalence scales provided by Statistics Netherlands for the Dutch data and the OECD equivalence scales for the U.S. data. The two equivalence scales are very similar to each other.

⁷Appendix E reports formal definitions of standardized moments and of the moments that we omit

coefficient of skewness

$$S_K = \frac{(P_{90} - P_{50}) - (P_{50} - P_{10})}{P_{90} - P_{10}}, \quad (1)$$

and the Crow-Siddiqui measure of kurtosis

$$S_{CS} = \frac{P_{97.5} - P_{2.5}}{P_{75} - P_{25}}. \quad (2)$$

Kelley skewness is positive (right skewness) if the probability mass between the median and the top decile exceeds the probability mass between the median and the bottom decile, while Crow-Siddiqui kurtosis, if large, denotes heavy tails, that is $P_{97.5} - P_{2.5}$ is large relative to the probability mass that is concentrated between P_{75} and P_{25} . For a normal distribution, Kelley skewness equals zero and Crow-Siddiqui kurtosis equals 2.91.

Quantile-based measures have the advantage of being both (i) easier to interpret and (ii) more robust to outliers than centered moment. We also report standardized third and fourth centered moments whenever they convey a qualitatively different picture than their quantile-based counterparts.

3 Results: Netherlands

In this section, we first study the properties of male earnings changes and the contribution of hours and wages to their dynamics. We then contrast the properties of male earnings, household earnings, and after-tax household income and discuss their implications for family and government insurance.

3.1 Male earnings, wages, and hours

3.1.1 Second moments

Figure 1 reports the standard deviation of male earnings (left), wage (middle), and hour (right) changes by percentile of previous earnings for various age groups. It reveals important patterns by age and previous earnings.

Focusing on age, the dispersion of earnings changes is particularly high for those in the bottom third of the previous earnings distribution in the youngest age group (25-34) and for those in the upper two thirds of the previous earnings distribution in the oldest

from the main text.

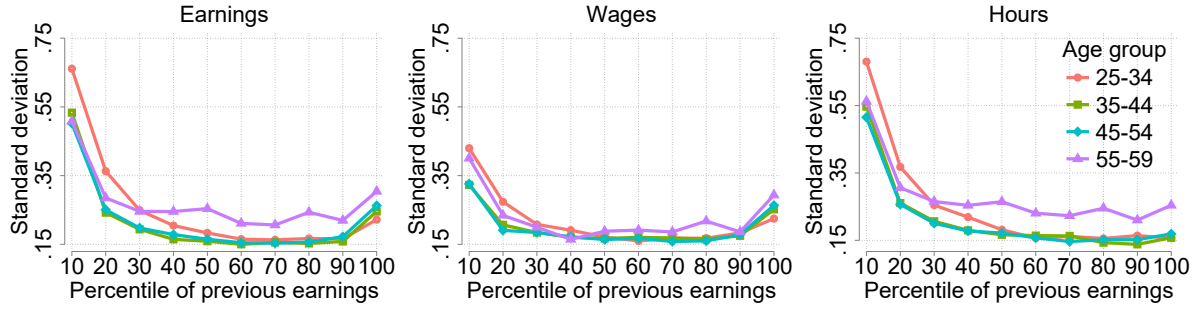


Figure 1: Netherlands: standard deviation of male earnings, wages, and hours

age group (55-59). This pattern by age is mostly driven by differences in the dispersion of hour, rather than wage, changes. Two institutional features of the Dutch labor market are likely important in generating these findings. First, flexible contracts are common among young workers and might generate more variability in their hours and earnings. Second, older workers are more likely to become eligible for partial disability benefits, which are reflected in the data as a reduction in hours whilst keeping the same wage.

The standard deviation by previous earnings displays a pronounced U-shaped pattern. It is more than twice as large for workers in the bottom decile of previous earnings than for workers around the median. Comparing it to the dispersion of wage and hours changes suggests that earnings fluctuations for lower earners are mostly accounted for by fluctuations in hours, be they temporary unemployment, demand-induced reductions in working time, or labor supply decisions. Workers with previous earnings above the 90th percentile also have higher dispersion of earnings changes than workers around the median, though substantially less than workers in the bottom decile. In the latter case, however, the pattern appears mostly due to a higher dispersion of wages, rather than hours, which likely reflects variable or performance-related components of earnings such as bonuses.

Simply comparing the variances of earnings, wages, and hours changes does not account for the potential correlation between wage and hours changes. Figure 2 decomposes the variance of earnings changes, across the distribution of previous earnings, into the contribution of the respective variances and their covariance. It confirms that the relatively higher dispersion of earnings changes for the bottom and top decile are mostly accounted by the higher relative variance of, respectively, hours and wage changes.

The covariance between wage and hour changes is negative throughout most of the

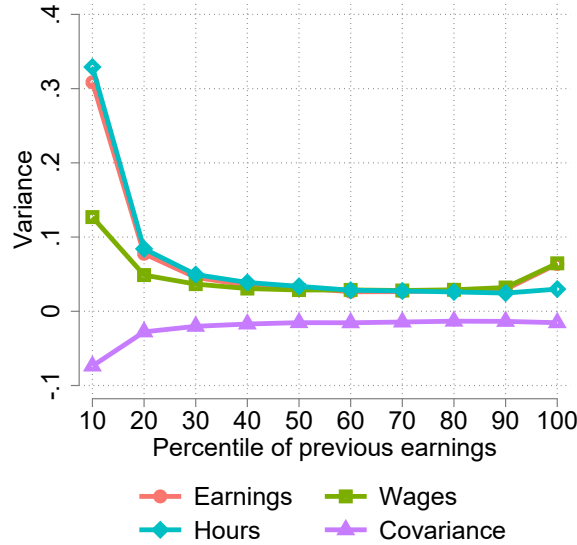


Figure 2: Netherlands: Variance of changes in male earnings, wages, and hours

distribution; it lies between -0.02 and 0 for all but the bottom two deciles. A negative covariance can be due to either measurement error in hours or to a strong income effect in labor supply (inter-temporal substitution elasticity smaller than one) that induces workers to increase hours in response to imperfectly insured falls in wages. Our finding that this covariance is more negative at low levels of previous earnings implies that measurement error would need to have a more elaborate form than classical in order to explain this feature of the data.⁸ Additionally, the fact that wages (which are constructed as earnings divided by hours) are less variable than both of the elements that are used to compute them suggests that it is unlikely that the negative covariance is a byproduct of significant measurement error in hours. In contrast, our observations are consistent with plausible economic forces. Namely, workers previously experiencing lower earnings are less able to self-insure through borrowing, more likely to need to finance a minimum level of consumption, and more likely to be on hourly contracts and thus are willing and able to increase hours to stabilize earnings in response to falls in wages. These considerations,

⁸We cannot rule out that low income workers, whose hours are more volatile, are particularly more affected by measurement error, which could increase the variance of their wage changes and make the covariance more negative. However, under the extreme assumption that the variance of true wage changes is zero, and as long as measurement error is uncorrelated with true hours and wage changes, the ratio between the variance of wage changes and hours changes (0.38 for the lowest decile) provides an upper bound to the contribution of measurement error to the observed variance of hours changes. In that scenario, it would still be the case that hours are much more volatile at the lowest decile than at the next.

together with the high reliability of our hour data (see Appendix A) indicate that this negative correlation between hours and wage changes in the Netherlands is consistent with economic mechanisms linked to a negative income effect, rather than merely being the outcome of measurement error.⁹

A complementary way of understanding the drivers of earnings changes is to decompose them into the contribution of wage and hours changes. Figure 3 reports this decomposition by plotting the (log) change in wage and hours on the vertical axis against the associated change in earnings on the horizontal axis. Each dot on a line represents a decile of earnings *changes*. The three panels refer to workers at three different points in the distribution of earnings *levels in the previous year*. Specifically, they refer to workers in the first, fifth and top deciles. For instance, the leftmost data point in the left panel of Figure 3 shows that workers in the lowest decile of previous earnings who experience the worst earnings change suffer on average an 80% decrease in their earnings (read off the horizontal axis). Of these, almost 70 percentage points are accounted for by a reduction in hours, and 10 percentage points are due to a reduction in wages (both read off the vertical axis). For these workers with low previous earnings, changes in hours are the major driver of all changes in earnings, independently of the size of the earnings change. The opposite is true for workers in the ninth decile of previous earnings (right panel) for which wages account for the larger share of all earnings changes. These are likely mainly full-time workers who remain in full-time employment and whose hours, therefore, vary much less. For workers at the median of the previous earnings distribution (middle panel), large negative earnings shocks are associated more with drops in hours (e.g., temporary unemployment) whilst positive earnings shocks are driven by changes in wages.

Finally, the right- and left-hand side panels of Figure 4 report the persistence, measured by the first-order autoregressive coefficient, of earnings and wage changes, respectively. Similarly to what Karahan and Ozkan, 2013; De Nardi et al., 2019 document for the U.S., in the Netherlands the persistence of earnings is lowest for the young and increases until about age 40 when it stabilizes. The same is true for wages, though their

⁹Averaging across the distribution of previous earnings the covariance between wages and hours is -0.02 which is in line with, but smaller in absolute value, than -0.04 (we compute such a value from the approximate correlation (-0.3) and variances of wage (0.15) and hour (0.1) changes taken from their Figure 2) reported by Heathcote, Storesletten and Violante (2014) for the U.S. PSID. They argue, quantitatively, that such a number is consistent with a model with endogenous labor supply in which the income effect is large and measurement error in hours is small.

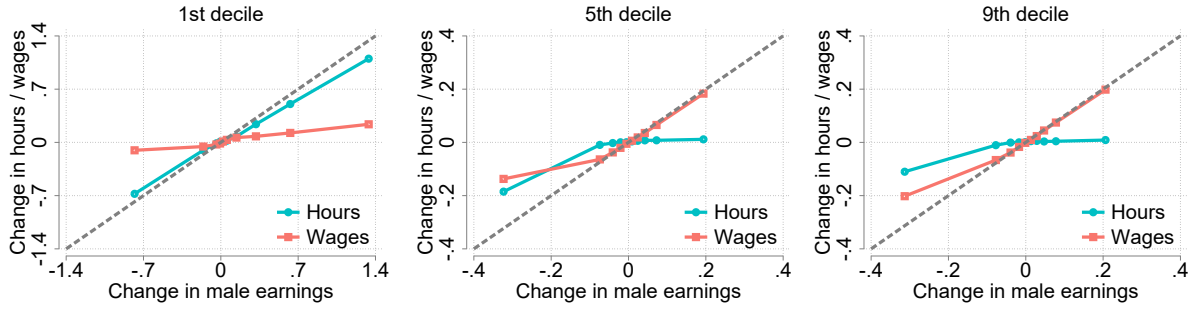


Figure 3: Netherlands: Male earnings changes versus hours and wage changes. Each dot represents a decile of changes in male earnings. The three panels represent, starting from the left, the first, fifth, and ninth decile of previous earnings, respectively

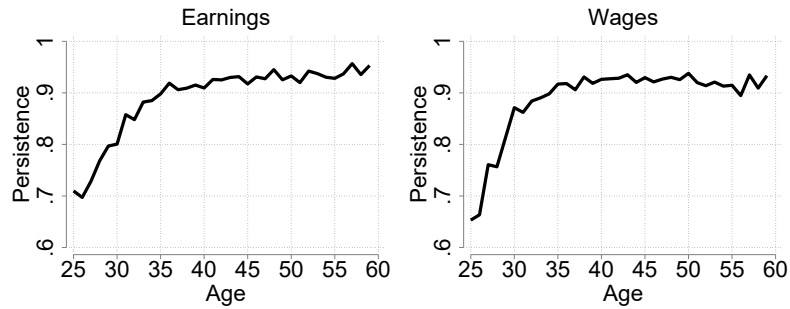


Figure 4: Netherlands: persistence of male earnings and wages as function of age

persistence is even lower until age 30, but then rises faster between 30 and 40.

In sum, male workers experience significant earnings variability, especially at lower levels of earnings and during the earliest and latest phases of the working life. This variability displays rich dynamics which, at low earnings levels, are mainly driven by the behavior of hours rather than wages.

3.1.2 Higher order moments

Turning to higher order moments, the first and second row of panels in Figure 5 study the asymmetry of the distribution of earnings, wages, and hours changes by reporting two measures of skewness: Kelley skewness (which is less sensitive to outliers) and the third standardized moment. For earnings, Kelley skewness is zero or positive for most age groups and for most of the distribution of previous earnings, with the noticeable exception of workers in the 55-59 age bracket, for whom it is significantly negative. Turning to wages and hours reveals that negative skewness is driven by the behavior of hours. Hours changes are more negatively skewed, particularly for the 55-59 age group, while wage

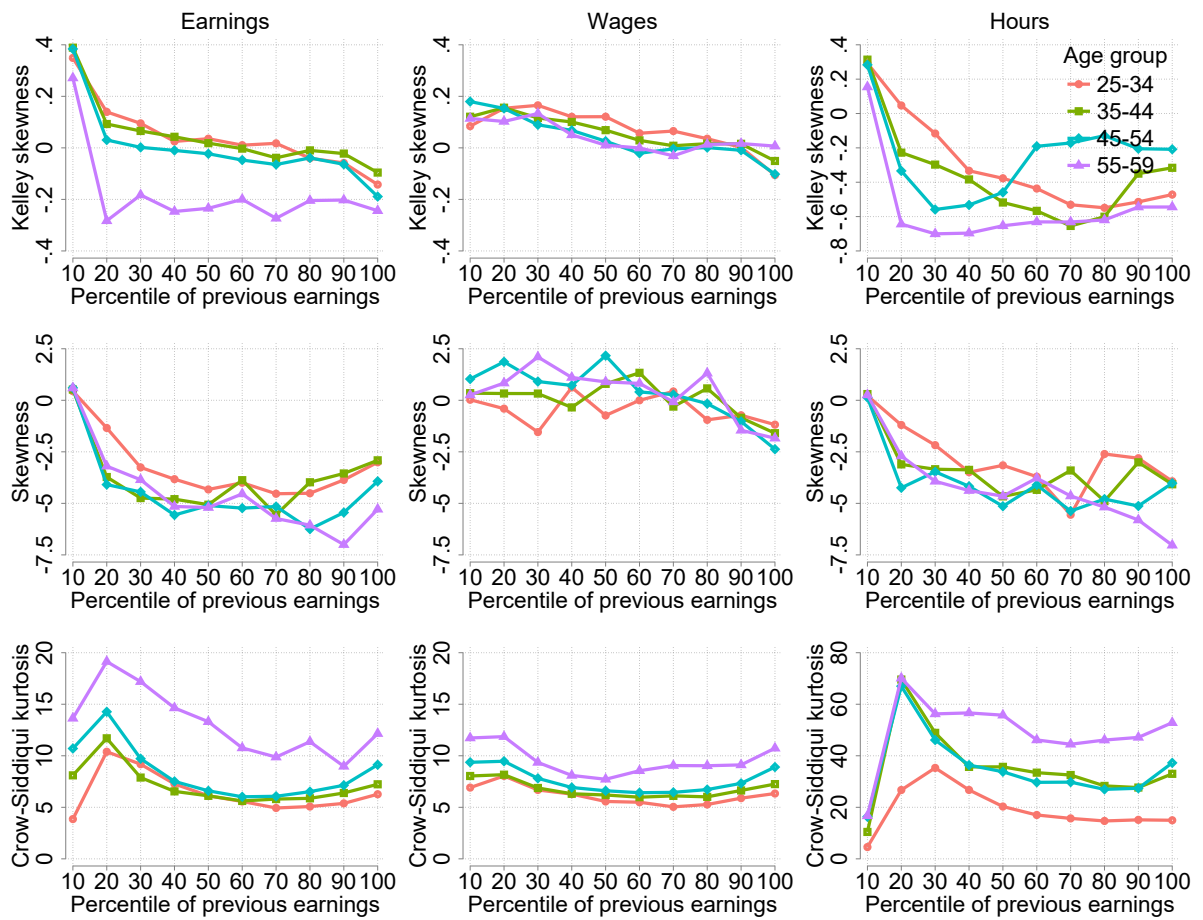


Figure 5: Netherlands: Skewness and kurtosis of male earnings, wages, and hours. Kelley skewness (top row), skewness (middle row), and Crow-Siddiqui kurtosis (bottom row)

changes are mostly positively skewed.

While Kelley skewness does not take into account asymmetries in the top versus bottom 10 percent of the distribution, the third standardized moment, reported in the middle row of Figure 5, provides a measure of asymmetry over the whole distribution. According to that metric, earnings changes display large and negative skewness.¹⁰ Comparing the skewness of earnings changes to that of wages and hours reveals that it is again hours, rather than wages that drive the negative skewness of earnings. The skewness of wage changes is mostly non-negative with the exception of workers in the top decile of previous earnings.

Finally, the last row of panels reports the Crow-Siddiqui kurtosis.¹¹ The kurtosis of earnings changes is highest towards the bottom of the distribution of previous earnings (up to the 20th percentile). The large kurtosis that we observe suggests that earnings shocks are very infrequent but that, when they happen, they tend to be of a large magnitude. This is particularly true for older workers, for whom employment protection is strongest in the Netherlands. Perhaps not surprisingly, kurtosis is even higher for hours than for earnings, suggesting that hour fluctuations are infrequent, but when they do happen they are relatively large (note the different scale in the graph).

As for the variance, comparing higher-order moments of earnings, wage and hours changes does not account for the co-movement between wage and hours. To address this, Figure 6 decomposes the skewness and kurtosis of earnings changes, as measured by the third and fourth standardized moments, into the contribution of the corresponding moments of wage and hours changes and their interaction. As far as skewness is concerned, the left panel in Figure 6 reveals that the negative skewness in earnings changes is mostly driven by changes in hours rather than in wages, while the contribution of the (negative) co-skewness is limited¹². Thus, the negative earnings skewness likely reflects persistent non-employment spells or reductions in the numbers of hours worked per week. This is

¹⁰This skewness, as measured by the third moment rather than by Kelley measure, is substantially more negative than found in Guvenen et al. (2015) for the US or Halvorsen et al. (2019) for Norway. This feature of the data is due to the fact that we plot the skewness of earnings over the distribution of earnings in the previous year, while these studies plot it over a measure of recent earnings that represents an average over the previous 5 years. As a result, our sample selection is less stringent (we only require earnings in t and $t-1$ to be above the minimum earnings level, and the ordering of percentiles is different). In Appendix D.2 we show that, using earnings over the last 5 years, skewness is much closer to the values found in those studies.

¹¹For completeness, Appendix E reports the centered Pearson's measure of kurtosis, which we do not include amongst these results for brevity.

¹²Appendix E.1 defines this decomposition, including co-skewness and co-kurtosis.

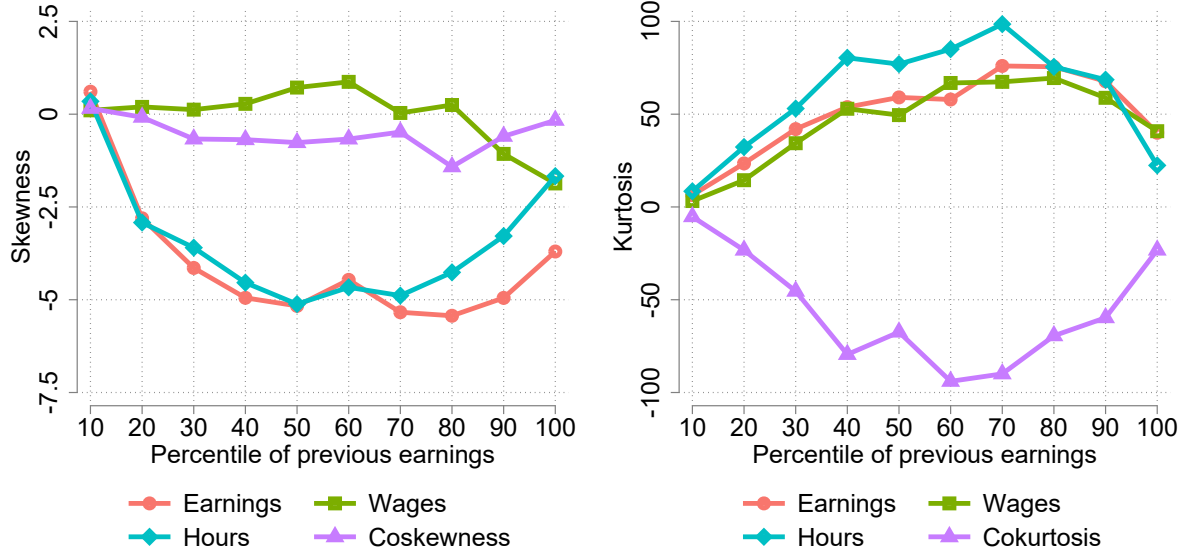


Figure 6: Netherlands: Skewness and kurtosis of changes in male earnings, wages and hours

consistent with the evidence presented in Hoffman and Malacrino (2019) for Italy,¹³ but at odds with the findings of Halvorsen et al. (2019) for Norway, where both the skewness of wage changes and co-skewness play a substantial role in explaining the negative skewness of earnings growth. These international differences suggest that the institutional framework that governs the labor market is crucial to determine the sources of earnings fluctuations and whether adjustment occurs at the hour or wage margin.

Finally, the kurtosis of earnings changes, reported on the right-hand-side panel of Figure 6, is driven by both hours and wages, although the contribution of hours is somewhat higher for individuals below the 90th percentile of previous earnings. Most individuals do not experience changes in either between one year and the next and this leads mainly to relatively small changes in earnings. As equation (6) in Appendix E.1 makes clear, the large negative co-kurtosis reflects that very large absolute changes in hours (wages) are associated with changes in wages (hours) of the opposite sign.

Taken together, these moments provide strong evidence in favor of age-variation, non-linearity, and non-normality of earnings changes and suggest that hours, more than wages, play an important role in the Netherlands.

¹³Hoffman and Malacrino (2019), as well as Busch, Domeij, Guvenen and Madera (2018) for Germany, are mainly concerned with the cyclicity of skewness. Yet, table A.3 in Hoffman and Malacrino (2019) reports the decomposition of the skewness of earnings changes in every year in their sample.

3.1.3 Separating days worked and hours per day

Our richer data starting 2006 (see Appendix A for details) allows us to further decompose yearly working hours between the number of days worked per year and the average number of hours per day worked. This decomposition (Figure 7) illustrates that most of the fluctuations are driven by the number of days worked, rather than changes in average hours per day. Thus, in the Netherlands, partial spells of unemployment or non-employment are the key drivers of the non-linear and non-normal patterns that we study. Changes in hours worked per day are less quantitatively relevant, with the only exception of lower-income workers (see left panel), for whom hour fluctuations within or across jobs are more frequent.

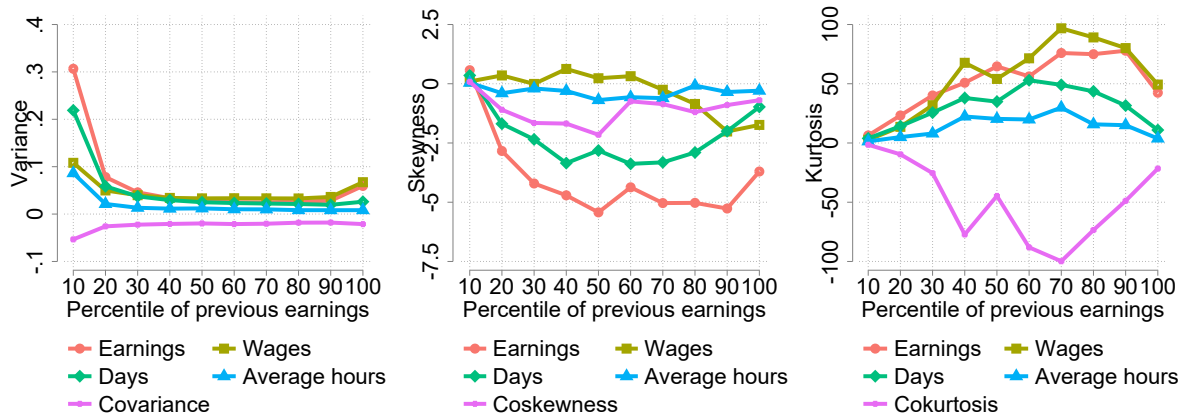


Figure 7: Netherlands: Decomposition of variance, skewness, and kurtosis, separating the role of days worked and hours worked per day. Days worked refers to the number of days, during the year, in which the employee was under an employment contract

3.2 Household insurance

Income pooling within households is a potential source of insurance against individual earnings fluctuations. There are two main reasons why a second earner can reduce the impact on household earnings of shocks to male earnings. The first is due to income pooling: a second earner being present implies that a share of household earnings is not affected by a change in male earnings. The second, often called the added worker effect, implies that the second earner might react to positive or negative shocks to her partner's earnings by changing participation or the number of hours worked.

We investigate the effects of insurance within the household, by comparing male versus

household earnings. The left and central panels in Figure 8 report moments for male and household earnings respectively.¹⁴ The top row of the figure shows that persistence is very similar for male and household earnings. Turning to the second row we can see that, among older workers, the standard deviation is a bit lower for household earnings than for male earnings and that, with the exception of younger households, Kelley skewness (third panel) is less negative for changes in household than male earnings. Interestingly, for younger workers in the top two thirds of the earnings distribution we find higher standard deviations and more negative Kelley skewness for household earnings compared with male earnings, which could be possibly be due to female spouses reducing working hours after the birth of a child.

The bottom two panels of Figure 8 show that the secondary earner plays an important role in reducing the impact on household earnings of *large* shocks to male earnings. Household earnings display substantially less negative skewness (as measured by the third standardized moment) and lower kurtosis than male earnings. This means that, at the household level, changes in earnings are relatively more frequent but smaller, while at the individual level changes in earnings are more infrequent but, when they happen, they are large. Thus, in the Netherlands the family plays a significant role in reducing the risks that households face.

Figure 9 disentangles the role of income pooling and added worker effects in generating within-household insurance. It reports the average change in women’s hours between years t and $t+2$, for those who were working in both years, as a response to changes in male earnings between t and $t+1$. Because women are typically the secondary earner, if there were an added worker effect, the number of hours worked by the woman in the household would respond to earnings shocks suffered by the man. By looking at two-year windows we can capture changes in female labor supply which are not exactly contemporaneous to the man’s earnings shock. We do not find any association between changes in male earnings and changes in women’s hours worked, indicating that it is mostly income pooling which explains the reduction in earnings risk at the household level that we have documented in the previous set of graphs. This is in line with findings for Norway (Halvorsen et al. (2019)), and may be due to correlated labour market opportunities of spouses. The only

¹⁴The sample pools single males and those who are cohabiting or married. Appendix D.4 shows that results are very similar if we just consider those who live in couples, who form the majority of our sample. Household earnings include adult children labor income whenever they are present in the household.

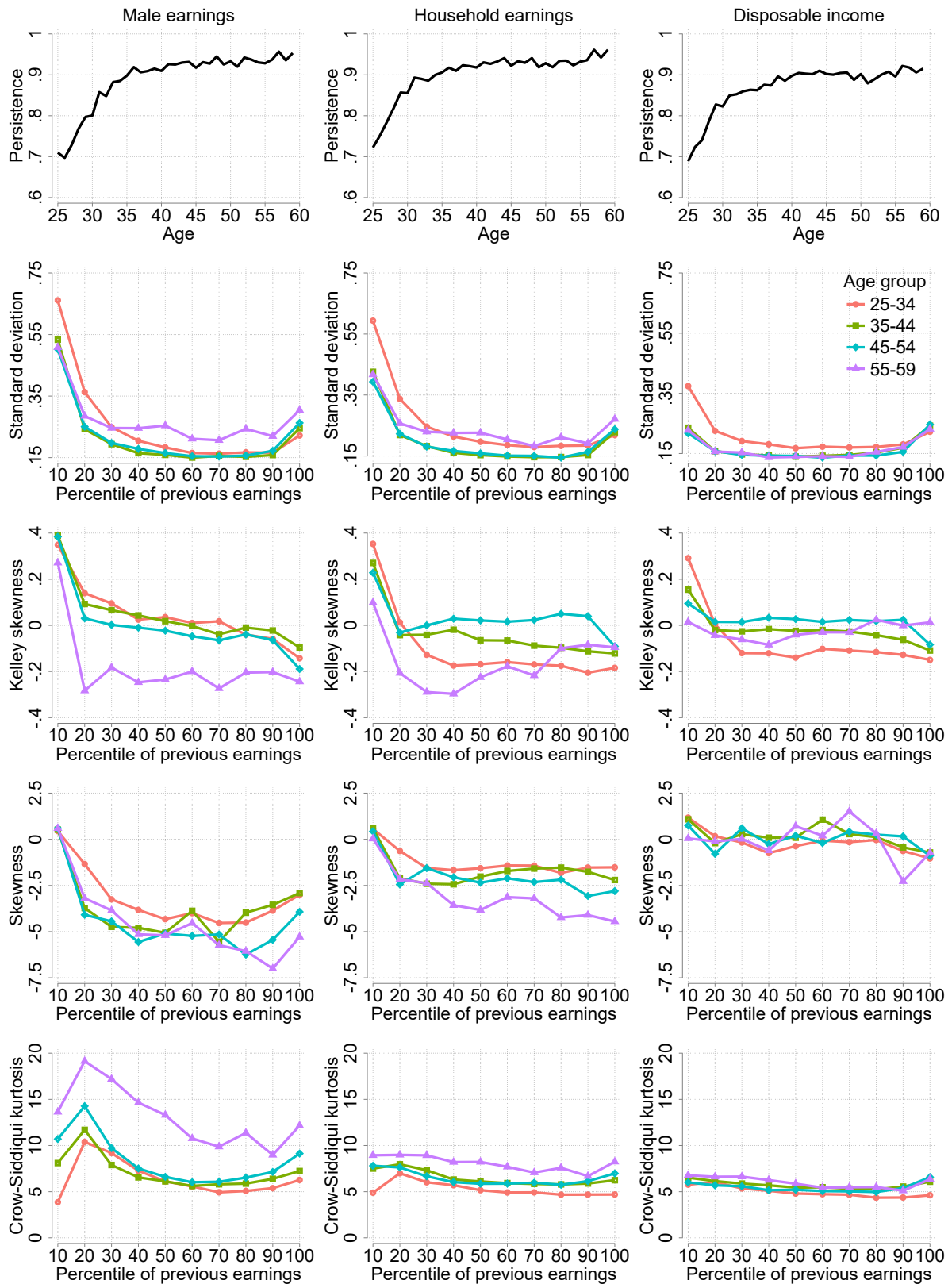


Figure 8: Netherlands: male earnings (left), household earnings (center), post-tax income (right). Persistence (top row), standard deviation (second row), Kelley skewness (third row), skewness (fourth row), and Crow-Siddiqui kurtosis (bottom row)

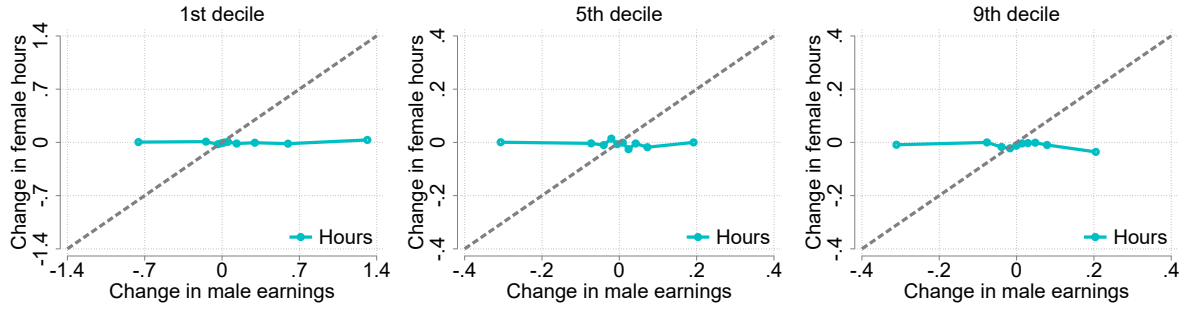


Figure 9: Netherlands: Male earnings changes and female labor supply. Each dot represents a decile of changes in male earnings. Lowest decile of previous male earnings (left), median decile of previous male earnings (center), 9th decile of previous male earnings (right)

noticeable, but small, labor supply reaction in the Netherlands is for women who reduce hours worked in response to large positive changes in male earnings, if the husband is in the top decile of the distribution of previous earnings (right panel). In Appendix D.5 we show that the same conclusions are true for contemporaneous hours changes of the spouse and her labor market participation decision.

3.3 Insurance from taxes and transfers

We also investigate the role of government insurance in reducing labor income risk. To this effect the central and right panels in Figure 8 report corresponding moments respectively for household earnings before taxes and benefits and disposable, after taxes and benefits, income.¹⁵

The comparison of the rightmost two columns in Figure 8 shows that taxes and transfers make a very large difference for the measures of risk that we focus on, especially at the lower end of the income distribution and for households in the oldest age group. Concerning disposable income, the standard deviations (second row of the figure) are lower and both measures of skewness (third and fourth row) become less negative relative to pre-tax household earnings. For instance, the standard deviation at the lowest percentiles of previous earnings declines from about 0.59 before taxes and transfers to a little over 0.37 after taxes and transfers. The reduction in the standard deviations and

¹⁵Household disposable income also contains net income from savings. This consists of the following components: interests from saving accounts and bonds, dividends, the rental value of the residential property, income from other real estate, income from other assets, and mortgage interest payments. It does not include capital gains from stocks or other financial assets. In Appendix D.3 we show that this capital income makes little difference for the dynamics of household income.

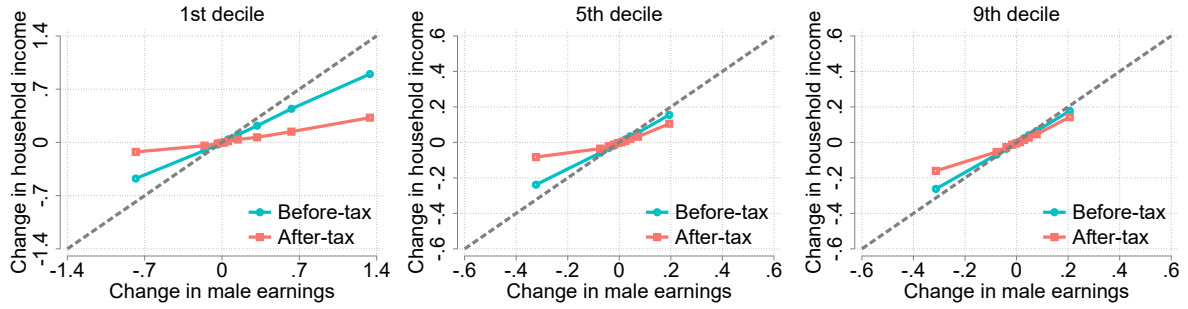


Figure 10: Netherlands: Household before- vs after-tax income. Each dot represents a decile of changes in male earnings. 1st decile of previous male earnings (left), 5th decile of previous male earnings (center), 9th decile of previous male earnings (right)

both measures of skewness is especially apparent for workers in the oldest age group. For them, skewness becomes almost zero. The Crow-Siddiqui kurtosis (fourth row) at the household level falls from about 8 before taxes and transfers (it peaked at about 17 for wages and male earnings) to well below 7 after taxes and transfers.

Figure 10 explores further the roles of household and government insurance by showing the pass-through of changes in male earnings to before- and after-tax household income. It shows that taxes and transfers offset positive and negative changes in male earnings, especially for households at the bottom of the distribution of previous earnings. For example, households in the first decile of previous earnings with a negative earnings shock of 80% experience on average a 50% drop in pre-tax household income, but only a 10% drop in disposable household income. Households in the fifth and ninth decile of previous male earnings experience smaller changes in male earnings (the dots are closer to zero). Households in the 9th decile of previous male earnings receive, as expected, less insurance from progressive taxation and transfers in case of a negative shock in male earnings (the difference between the slopes of the blue and the red lines is smaller). Instead, positive shocks in male earnings are also more cushioned by the government for households in the first decile of previous male earnings (most likely reflecting benefit withdrawal), compared with households in the fifth and ninth decile of previous male earnings.

Given that government insurance is especially prevalent in the Netherlands and especially so at older ages, Figure 11 further breaks down the role of various government programs for our 55-59 age group by sequentially adding specific transfer programs and taxes. The graphs show that disability insurance greatly reduces the standard deviation of household earnings changes below the 20th percentile of previous earnings, while un-

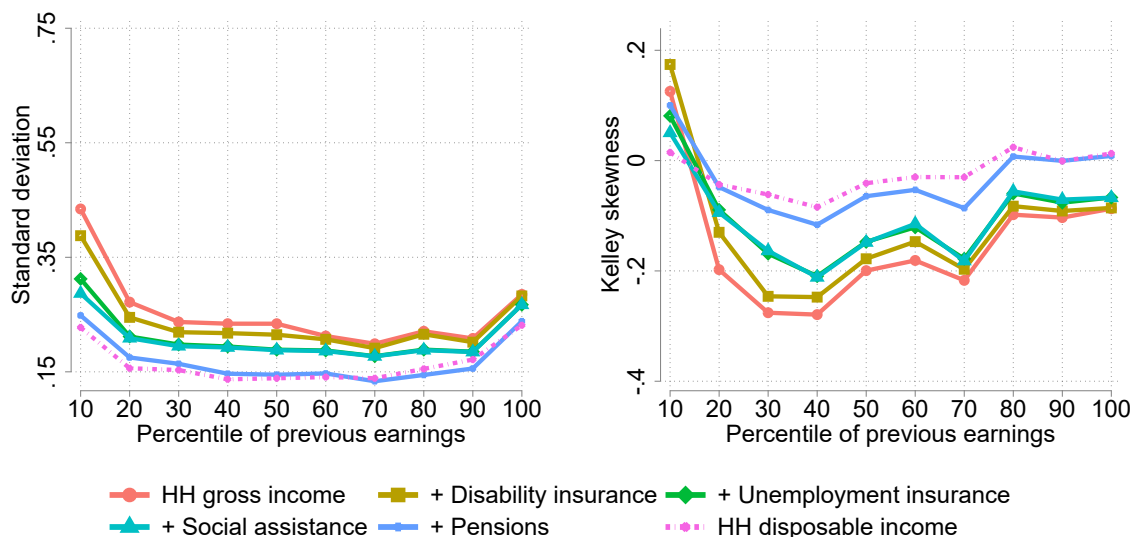


Figure 11: Netherlands, age 55-59: Relative contribution of transfers and taxes to the standard deviation of household income. Red line, household gross income, gold line: including disability insurance, green line: also including unemployment insurance, dotted green line: also including social assistance, dotted blue line also including pensions, dotted red line: also net of taxes

employment insurance generates a significant reduction even at higher levels of previous earnings. It also shows that, for this age group, (early) retirement transfers, associated with early access to occupational pensions, play a much larger role in reducing variation in household income than progressive taxes. The right-hand-side graph of Figure 11 shows that negative skewness is largely offset by taxes and transfers.

Our analysis makes it clear that the government and private pensions provide a lot of insurance in the Netherlands. Progressive taxation reduces earnings variability and the benefit system (unemployment insurance, disability insurance, and welfare) and early access to occupational pensions reduce income variability. In particular for older workers and for the bottom of the distribution of previous earnings, transfers effectively eliminate large negative shocks, such that negative skewness disappears and the kurtosis is reduced. The breakdown of transfer programs or taxes suggest that progressive taxation plays less of a role in reducing earnings variability.

4 Results: Netherlands versus U.S.

While Section 3 focuses on risks and insurance in the Netherlands, this section compares risks and insurance in the Netherlands and the U.S. Figure 12 reports our summary statistics for the Netherlands (left) and the U.S. (right), pooling across all age groups for clarity. A first noticeable feature is that the standard deviations of wages, hours, earnings, household income and disposable income are, respectively, much larger in the U.S. than in the Netherlands.

Looking more into the top panel and comparing male wages to earnings also reveals that moments for earnings and wages are substantially closer to each other in the U.S. data than in the Dutch data. To better understand this phenomenon, Figure 13 decomposes the relative contributions of hours and wages to second and higher moments of earnings changes in the U.S. Its left panel shows that, in the U.S., the variance of wages is much closer to that of hours (compare with Figures 2 and 6), suggesting that wage adjustments are more frequent in the U.S. than in the Netherlands. Its center and left panel highlight that in the U.S. too hours are the largest contributor to skewness and kurtosis.¹⁶ It is worth noting that hours are measured less precisely in the PSID data than in our Dutch data and this might affect some of these results.

Turning back to Figure 12 and comparing male to household earnings reveals a larger role for spousal insurance in the U.S. in terms of reducing the standard deviation and skewness of male earnings at all levels of previous earnings. The presence of spousal earnings tends to compress both the volatility and the tails of the household earnings distribution in the U.S (in line with Pruitt and Turner (2018), who use administrative data from the U.S.). These patterns are present in both countries, except that in the Netherlands Kelley skewness becomes more negative after including spousal earnings.

Finally, comparing gross to disposable income reveals that while government insurance reduces the variability and negative skewness of earnings changes in both countries, this role is much larger in the Netherlands and particularly so for households at the bottom of the (previous) earnings distribution.

¹⁶We report centered kurtosis in Appendix E.

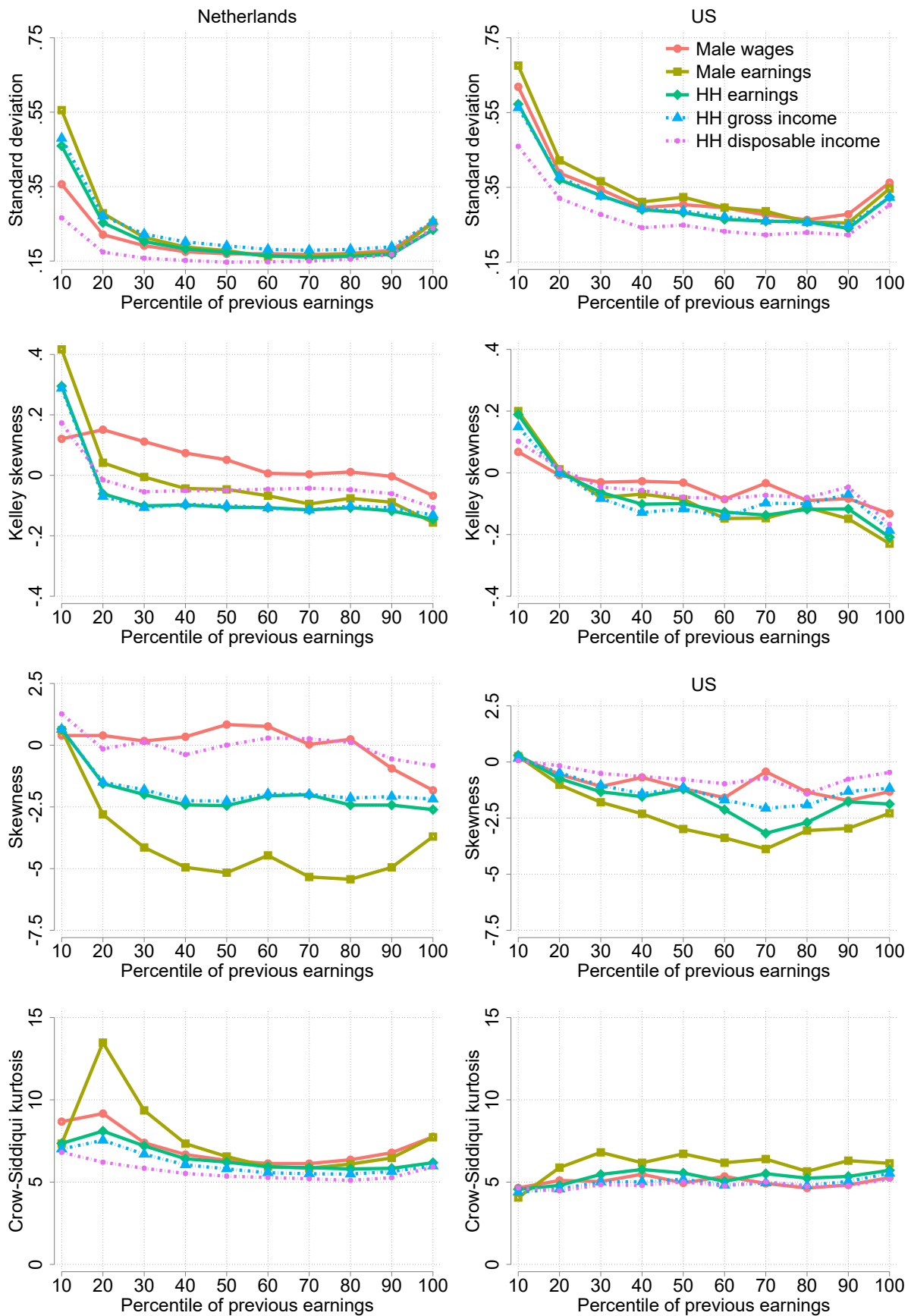


Figure 12: Summary statistics for various income definitions, by previous earnings. Netherlands (left), U.S. (right)

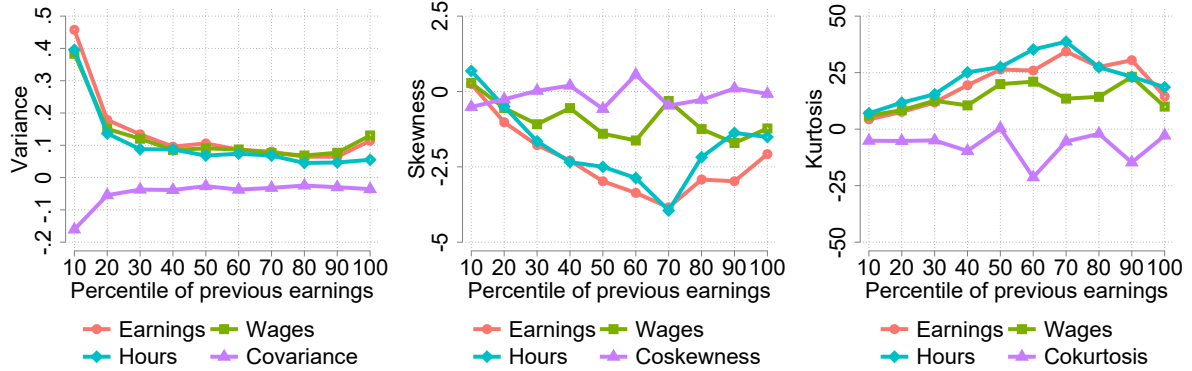


Figure 13: U.S.: Variance, skewness and kurtosis of changes in male earnings, wages and hours

To confirm that results are driven by cross-country differences and not by period of observation, we also examine income dynamics for the PSID in the post 1997 period, which covers the same time frame as the IPO data. The results are very similar (Appendix D.1), thus indicating that the results are mainly driven by cross-country differences rather than by different time periods.

To evaluate whether our cross-country comparison is affected by the fact that we use administrative data for the Netherlands and survey data for the U.S., we also compare Dutch survey data (DHS) with those from our administrative Dutch data. Most of the patterns across the income distribution are similar (see Appendix C). The main differences are that, in the survey data, the differences between pre-tax income and disposable income are smaller, and the role of wages in earnings dynamics are larger than in our administrative data. Given that wages are constructed by dividing earnings and hours, and that the survey data do not account for the number and duration of employment spells in a year, this is likely to be related to measurement error in changes in hours worked in the survey data. Thus, our results suggest that properly capturing employment spells is crucial to properly decompose earnings fluctuations between hours and wages.

5 Conclusions

We study the nature of labor income risk in the Netherlands and the U.S. For the Netherlands, we use high-quality administrative data to disentangle the contribution of wages

and hours to the dynamics of male earnings. Furthermore, we investigate the degree of insurance provided by spousal labor supply and by the tax and transfers system in both countries.

We document that the dynamics of individual male earnings is similar in both countries and displays important deviations from the typical assumptions of linearity and normality. Individual-level male wage and earnings risk is relatively high at the beginning and end of the working life, and for those in the lower and upper parts of the income distribution. Importantly, we find that hours are the main driver of the negative skewness and, to a lesser extent, the high kurtosis of earnings changes. In the Netherlands, hours also account for most of the variability of earnings for workers in the bottom two deciles of the earnings distribution.

Turning to family and government insurance, in the Netherlands women's earnings reduce the standard deviation of labor income risk at the household level only if the husband's earnings are in the bottom third of the earnings distribution. Indeed, for the age group 25-34 the variance of household earnings exceeds that of the husband's earnings if the latter are in the top two-thirds of the distribution. This is probably due to the birth of children. However, income pooling within the household makes skewness substantially less negative, thus suggesting that the presence of a secondary earner in the household can smooth out large negative shocks. This effects appear stemming from income pooling alone, as we do not find evidence of an added worker effect in the Netherlands.

Comparing family and government insurance we find that the government plays a much larger role in reducing wage risk in the Netherlands compared with the U.S. A breakdown in government programs for older workers in the Netherlands shows that DI and UI programs reduce income risk, especially for the lowest quarter of the male earnings distribution. Pensions and taxes (to a lower extent) reduce earnings risk across the whole distribution. Instead, in the U.S. the role that the family plays is much more important. The results suggest that taxes and transfers may crowd out insurance that could be generated within the family.

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Appendix

A The hours data

We obtain the data on hours worked by linking the IPO data with data from the Dutch payroll administrations (DPA). To assess the quality of the data, this appendix describes the data collection process and the importance of this data for various benefit systems.

Dutch legislation mandates that all employers maintain up-to-date payroll records. These records include employment start and end dates (and thus total number of days employed), number of regular and overtime hours, and earnings. Most employers outsource the payroll administration and about 60% of pay slips are handled by four big companies: Raet (25%), LogicaCMG (19%), ADP (11%) and PinkRocade (6.6%). These companies provide monthly pay slips to employees. The same software systems also provides an automatic report to the government each month. Therefore, if a pay slip contains a mistake and the employee complains, a correction in the software system is made and passed on to the government.

The number of hours worked on an employee's monthly pay slip matters for annual leave computations, the duration of parental leave, pension contributions, pension accrual, the eligibility and duration of unemployment and disability benefits, and child care allowances. Thus, both employees and employers have strong incentives to check that employment spell dates and hours worked on their pay slips are correct.

With respect to annual leave, part-time workers usually receive a reduced number of days. This also holds for parental leave time, which corresponds to 26 times the number of weekly hours worked.¹⁷

Employers also have to send payroll records to pension funds because hours worked (technically, part-time factors, i.e., the ratio of an employee's hours worked to the usual working time in a sector) and employment spells are needed to compute pension contributions and pension rights accumulation. Overtime work by part-time workers up to a full time workweek is taken into account in the computation of pension contributions and pension rights. When part-time and full-time workers work more than full time, whether overtime work in excess of full time hours leads to higher pension contributions

¹⁷During parental leave employees keep the same part-time factor, but gross and net salary are often reduced. This implies a measured wage drop for people on parental leave. The same holds for sick leave.

and higher pension entitlements depends the pension plan's rules.

Furthermore, working hours and employment spells play a role in the Dutch UI and DI system. People are entitled to unemployment benefits if they a) Lose at least 5 hours of their labor hours per week. In case someone works less than 10 hours per week, he or she becomes unemployed when he or she loses at least half of the working hours. For example, if someone works 8 hours per week and loses 4 hours, he or she is unemployed. b) Have worked at least 26 weeks out of the 36 weeks (in 2014) before becoming unemployed. The requirement on the employment spell that we discuss in point (b) also holds for disability insurance. Moreover, the duration of UI and DI benefits depends on employment history.

Finally, the part-time factor is important for the number of hours that people receive as child care allowance. The beginning and end dates of an employment spell are also important for child care allowances, because people lose the entitlement to child care allowances after a period of unemployment.

Figure 14 shows an example of a pay slip, with 6.67 hours of overtime work. In jobs that offer overtime pay, the worker has an incentive to verify whether the number of overtime hours is not understated and the employer has an incentive to check that the number of overtime hours is not overstated.

Salarisspecificatie		Datum	Periode
		31-01-2017	1
Mevrouw Vader, A Zuideinde 489 1035 CW Amsterdam		Active BV Dam 2 1506 ED Zaandam	
Loonheffingsnummer 131459077L01			
Loon januari 2017	€	3.000,-	
6,67 Overwerkuren t.g.v. meeruren	-	115,38	
	€	3.115,38	
Inhoudingen:			
loonheffing met loonheffingskorting	€	827,33	
0,245 % W.G.A.	-	7,63	
	€	834,96	-/-
Netto loon, met loonheffingskorting	€	2.280,42	
€ 2.280,42	Betaald op rekeningnummer	NL42INGB0005510125	
Werknemergegevens			
Besteller		060316573	
BSN		18-01-1963	
Geboortedatum		01-01-2005	
Datum in dienst		€ 17,31	
Durloon		€ 1.551,60 (23+)	
Minimumloon		Wit	
Tabel		Met loonheffingskorting	

Figure 14: Example of a pay slip

Hence, several mechanisms ensure the quality of the data. Because remaining errors are still possible, the employment office performs several additional checks and amends the data in case of errors.

The resulting data are exceptional, and particularly suitable for our purposes, because they capture extremely well even those employees that have irregular patterns of employment. For instance, in 2013, 15% of all employees had more than one job, 12% worked for more than one employer, and more than 7% worked for more than one employer in the same month (most of them simultaneously). As we see in the figures that follow, many employees do not work full time and many employees do not work the whole year. Capturing the exact duration of labor market spells for irregular employees is particularly difficult in survey data and some administrative data sources, and can introduce substantial measurement error if a noisy measure of hours is used to compute wages using earnings, which tend to be more precisely measured, particularly if they come from tax records.

We have access to all of this information from 2006 onwards, while slightly more aggregated data are available since 2001. To have a longer sample period, we report the results with the less aggregated data in the main body of the paper, while B we report results using data from 2006 onwards only. All economic implications are the same.

More specifically, the 2001-2005 data include the total number of *employed days* and *full-time equivalent hours*. The total number of *employed days* measures the calendar days that the individual was covered under a certain employment contract. An employee is said to be a worker in a given day if he or she was working, on holiday or other (un)paid absence, and this applies both to part-time jobs and full-time jobs. The *full-time equivalent hours* measure is the result of, at a yearly level, aggregating the total number of hours worked, converting it to days, and dividing it by the number of employed days. The total number of hours worked in a year can be obtained by multiplying full-time equivalent hours and the number of employed days. The full-time equivalent hours measure includes workers working overtime or having two contracts at the same time, even if these sum up to more than 40 hours a week, and workers working part-time, and averages them out across the year.

There are two caveats with the full-time equivalent hours measure in the 2001-2005 data. The first is that it is restricted to be at most 1 for an individual in a calendar year. Thus, while it would be 1 for an individual that worked 85% of a full-time job for 6 months and 115% of a full-time job for 6 months, and it would be 1 for an individual that worked a full-time job the whole year, it would also be 1 for an individual that worked

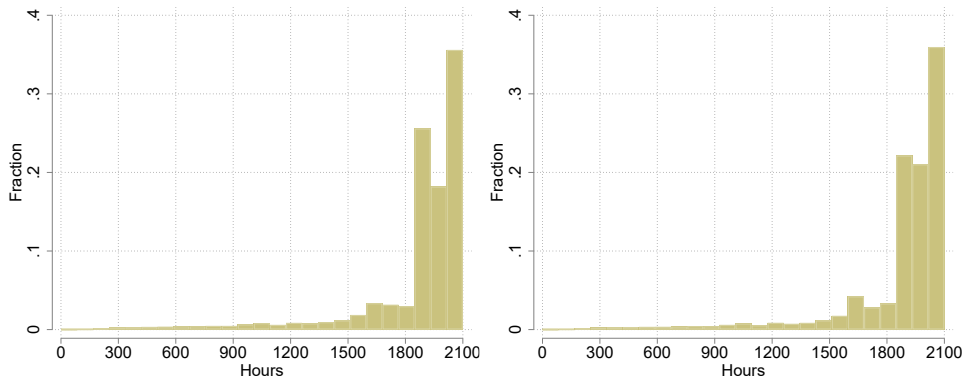


Figure 15: Netherlands: Total hours worked, 2001-2014 dataset (left), 2006-2014 dataset (right)

for 115% of the time for a whole year. The second caveat is that the full-time equivalent hours measure is defined to be 1 if an employee works the (usual) number of weekly working hours according to the Collective Labour Agreement (CAO) of a business sector. For firms without a CAO a full time contract is defined as the most common number of hours worked in the firm surpassing 34 hours: Dutch law recognizes full-time employment from 36 to 40 hours per week. We use sectorial information and the post-2006 data to impute the length of a full-time week for each sector. Thus, our final hours measure for our main results is the result of multiplying the length of a full-time week by the number of employed days divided by 7, by the full-time equivalent measure, which is between 0 and 1.

Our richer data starting in 2006 is not affected by either of these two limitations, and thus we use it to evaluate their impact on our results. Figure 15 compares both variable definitions by showing the histogram of hours worked for the 2001-2014 dataset and the richer post-2006 data. Both datasets capture regular and overtime hours until one full-time year. However, only the post-2006 data captures overtime hours for full-time workers. Figure 16 shows the distribution of overtime hours in the rich post-2006 dataset. Since this paper is about income dynamics, Figure 17 shows histograms of hours *changes* using both definitions: whilst the post-2006 data is better suited to capture small fluctuations of hours around zero, which implies a lower central peak, both distributions of changes in hours worked are very similar.

A comparison of the 2001-2014 data with the post-2006 data thus show that these data are very similar and that both of these measures capture very well all patterns of

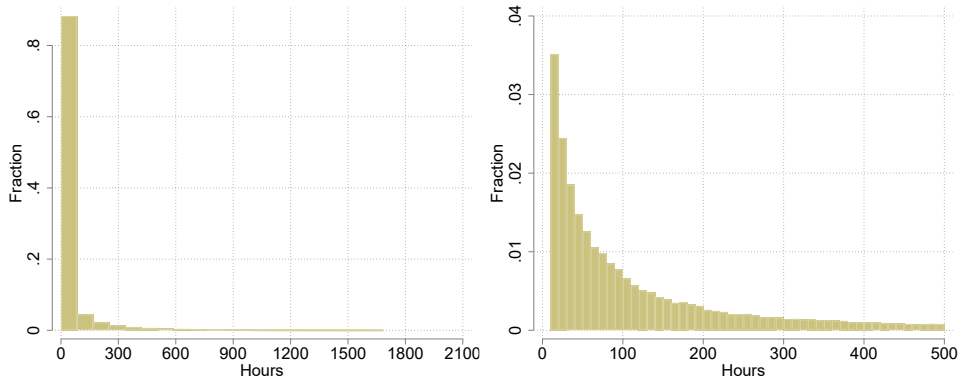


Figure 16: Netherlands: Overtime hours, richer measure of hours since 2006. Right panel is a zoomed-in version of the left panel for clarity

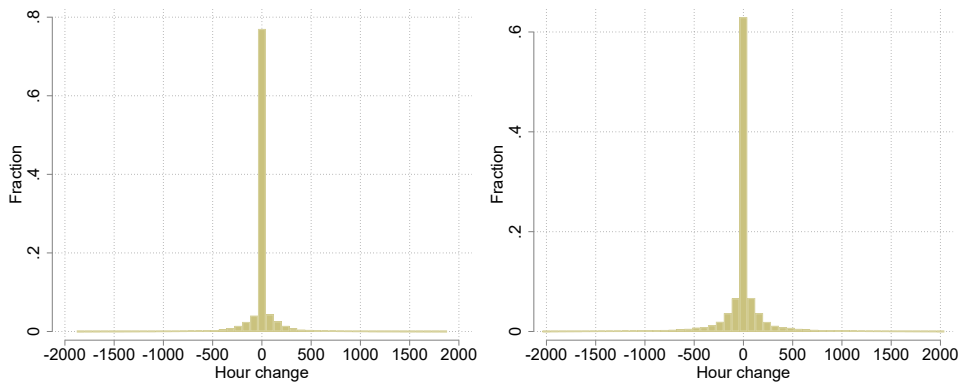


Figure 17: Netherlands: Change in hours worked, 2001-2014 dataset (left), 2006-2014 dataset (right)

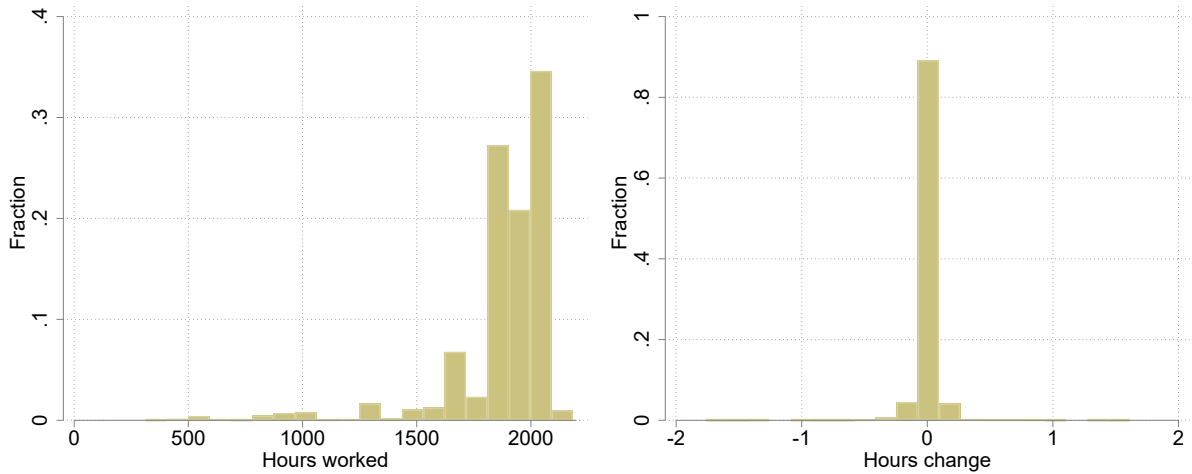


Figure 18: Netherlands: Total hours worked and change in hours worked, DHS survey data 2001-2014

irregular employment, part-time work, workers with multiple jobs, and so on, that are at the core of the wage dynamics we seek to explain.

To compare our measured hours with those from survey data, Figure 18 shows the histograms of hours worked and changes of hours worked implied by the Dutch DHS household survey. As many household surveys, the DHS survey only asks about hours worked in a typical week, and yearly hours can only be generated by multiplying that number by 52. Thus, this measure captures improperly both those workers for whom the typical working week has changed over the year and those who have had spells of unemployment. This is reflected in higher bunching in the histogram for hours worked and hours change.

B Results for the post-2006 data

From 2006 onwards, we have access to the complete payroll records for each employee, and thus have as accurate information on hours as possible. For the period before 2006, Statistics Netherlands provides researchers with a summary measure of hours that has two limitations: (a) it is normalized by “typical” working hours in a sector and (b) it is capped at full time hours. In our main results we use this latter version of the data. We address the first limitation of the pre-2006 data by computing the typical workweek in each sector in the post-2006 data and using it to re-normalize the data for each sector in the pre-2006 data. Concerning the cap at full-time hours, it constrains the measurement of overtime hours for full-time workers, but not for part-time workers, as long as the total number of hours worked does not exceed full time hours.

To evaluate the effects of missing overtime hours for full-time workers before 2006, this appendix compares our results for our complete sample period with those we obtain using only the post-2006 sample period. As we can see below, the results are extremely close.

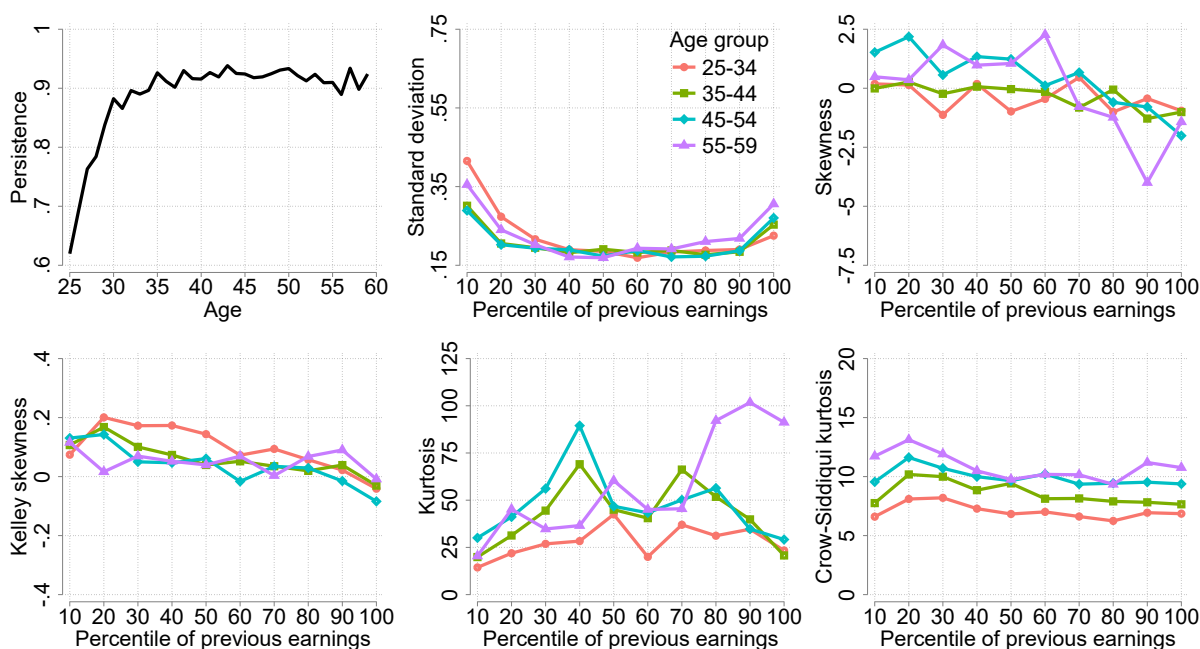


Figure 19: Netherlands: Male wages, computed using actual hours worked. Wage persistence (top left) and following moments of wage changes: standard deviation (top middle), skewness (top left), Kelley skewness (bottom left), kurtosis (bottom middle), and Crow-Siddiqui kurtosis (bottom right), by age group and previous earnings percentile. Post-2006, richer hours data

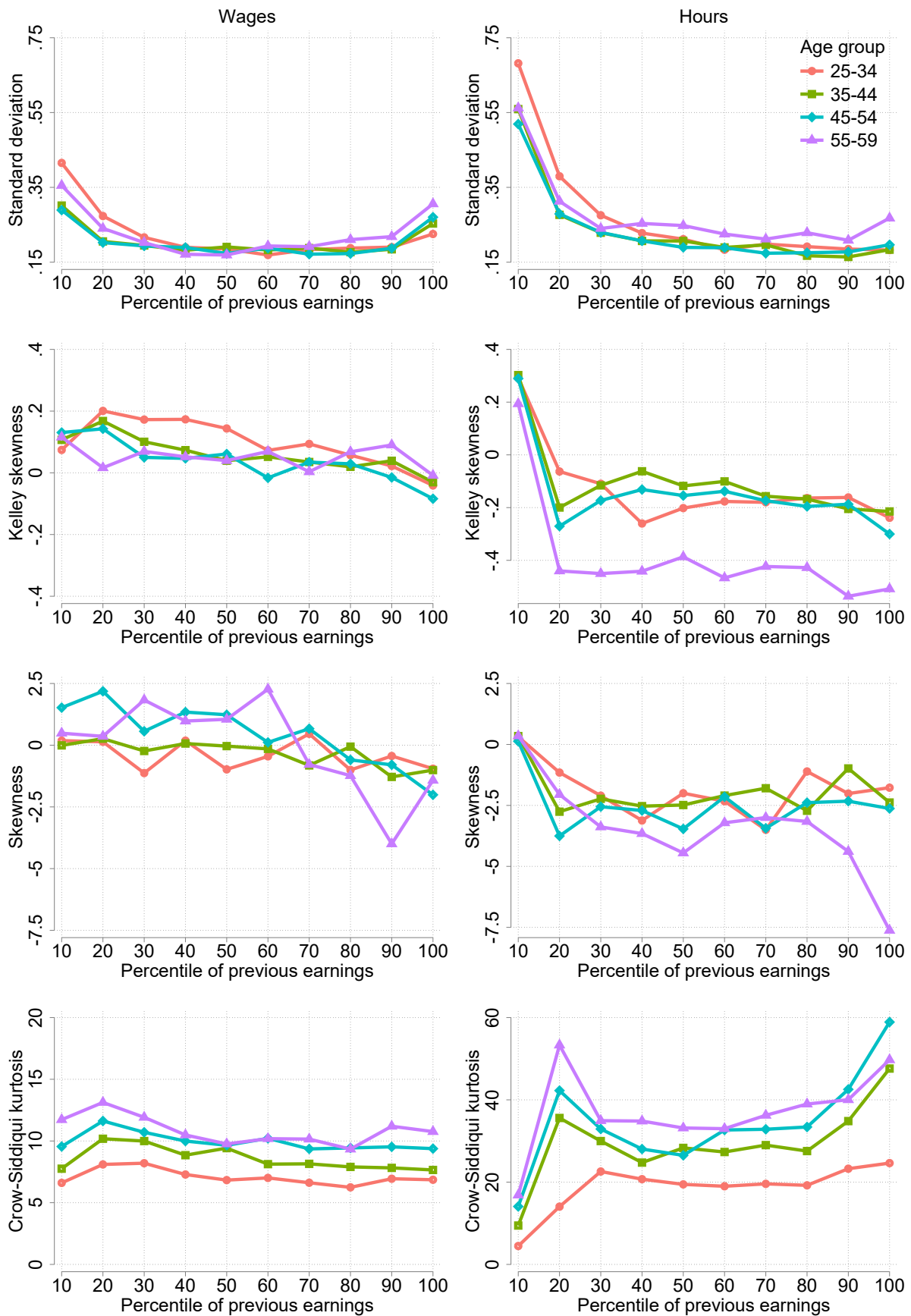


Figure 20: Netherlands: Male wages (left), and male hours (right). Standard deviation (top row), Kelley skewness (second row), skewness (third row), and Crow-Siddiqui kurtosis (bottom row). Post-2006, richer hours data.

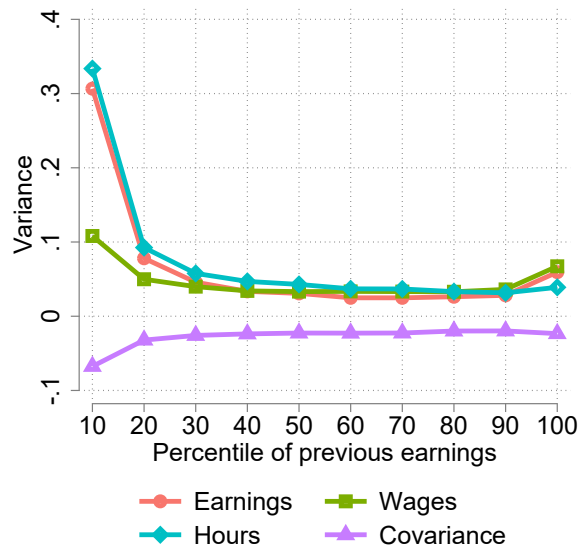


Figure 21: Netherlands: Variance of changes in male earnings, wages and hours. Left: all workers; middle: workers with a positive hours change; right: workers with a negative hours change. Post-2006, richer hours data

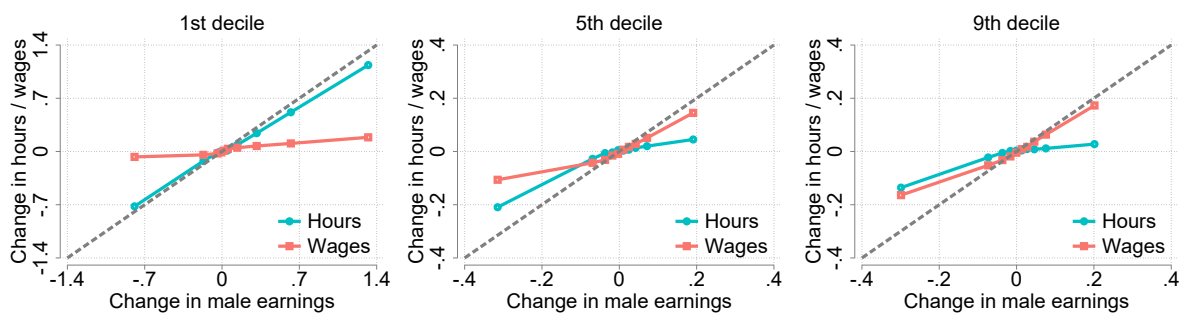


Figure 22: Netherlands: Male earnings changes versus hours and wage changes. Each dot represents a decile of changes in male earnings. 1st decile of previous earnings (left), 5th decile of previous earnings (middle), 9th decile of previous earnings (right). Post-2006, richer hours data

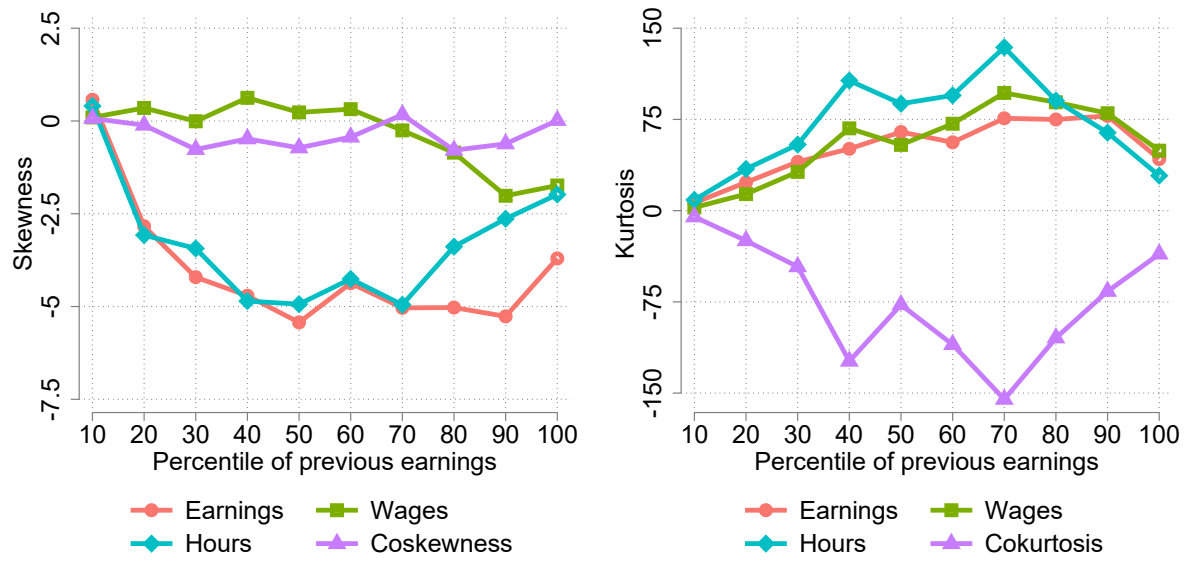


Figure 23: Netherlands: Skewness and kurtosis of changes in male earnings, wages and hours. Post-2006, richer hours data

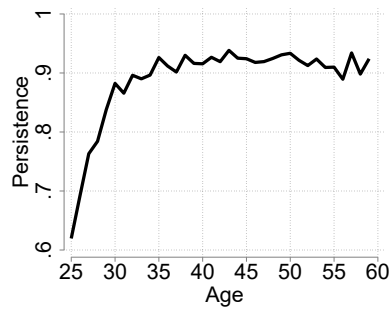


Figure 24: Netherlands: persistence of male wages as function of age. Wages computed with richer. Post-2006, richer hours data

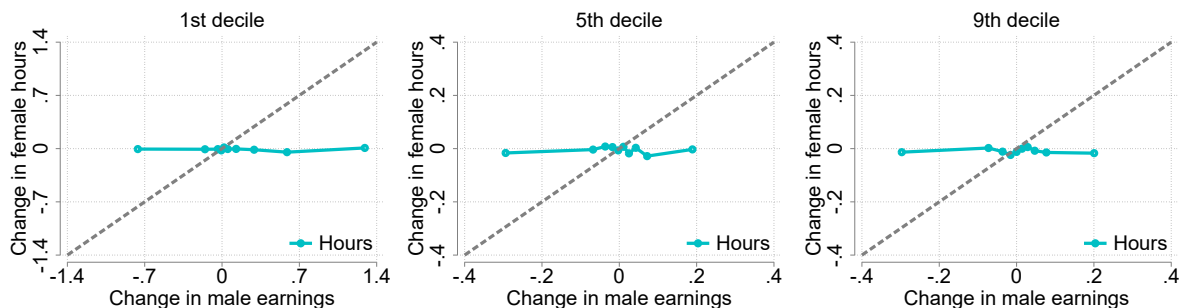


Figure 25: Netherlands: Male earnings changes and female labor supply. Each dot represents a decile of changes in male earnings. Lowest decile of previous male earnings (left), median decile of previous male earnings (center), 9th decile of previous male earnings (right). Post-2006, richer hours data

C DNB household survey (DHS)

This section reports the same labor income moments in Section 4 but computed using household survey, rather than the administrative IPO, data for the Netherlands. The survey data come from the DNB Household Survey (DHS) which is a representative Internet-based panel of over 2000 households administered by CentERdata at Tilburg University and sponsored by the Dutch Central Bank (DNB). It contains detailed information on components of personal and household income.

We use the DHS to confirm that the patterns that we document for the Netherlands in our administrative data set also hold in survey data for the Netherlands over the same, 2001 to 2014, period. Comparing Figure 26 below to the left-hand panels in Figure 12 in Section 4 reveals that patterns are very similar across the two datasets. Only, the role of wages in earnings dynamics is larger in the survey data than in the administrative data. As the DHS does not allow us to account for unemployment spells during the year, this is likely to be related to measurement error in changes in hours worked in the survey data. In line with this, the skewness of hours worked is more negative in the administrative data (Figure 6) than in the survey data (Figure 27).

Given that our data for the U.S. comes from a household survey, this reassures us that the differences that we document across countries are not due to the nature of the data set but rather to institutional differences across countries.

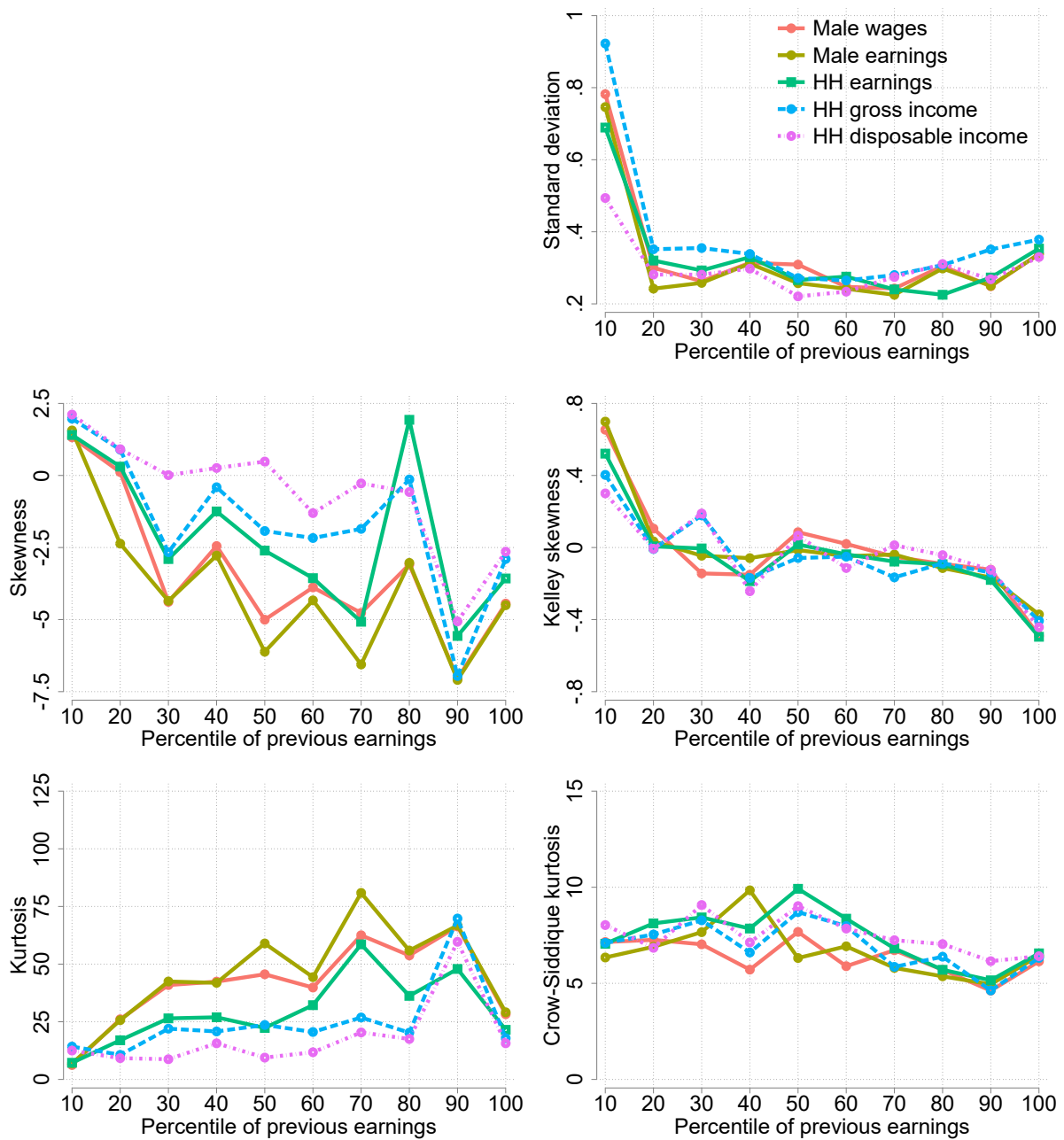


Figure 26: Netherlands: DNB Household Survey (DHS). Summary statistics of various income definitions, by previous earnings

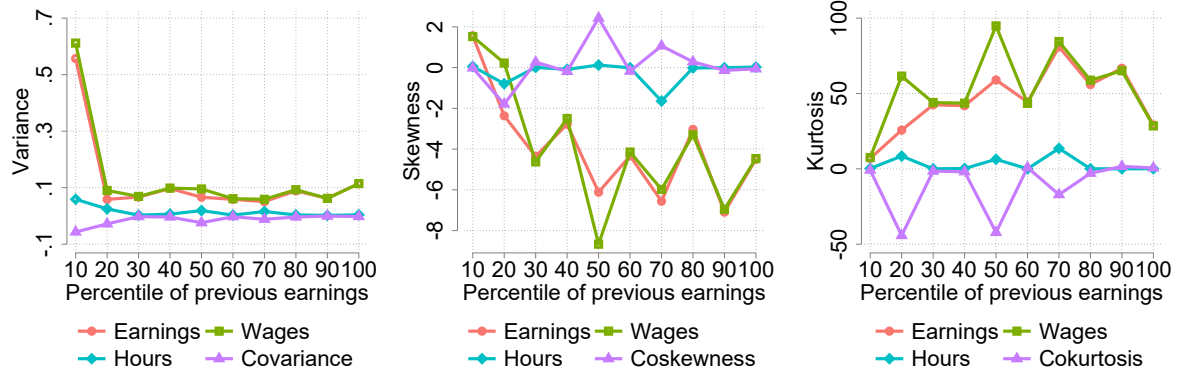


Figure 27: Netherlands: DNB Household Survey (DHS). Decomposition of variance, skewness, and kurtosis of earnings, by previous earnings

D Alternative sample selections and variable definitions

D.1 Two-year changes in the Netherlands and the U.S.

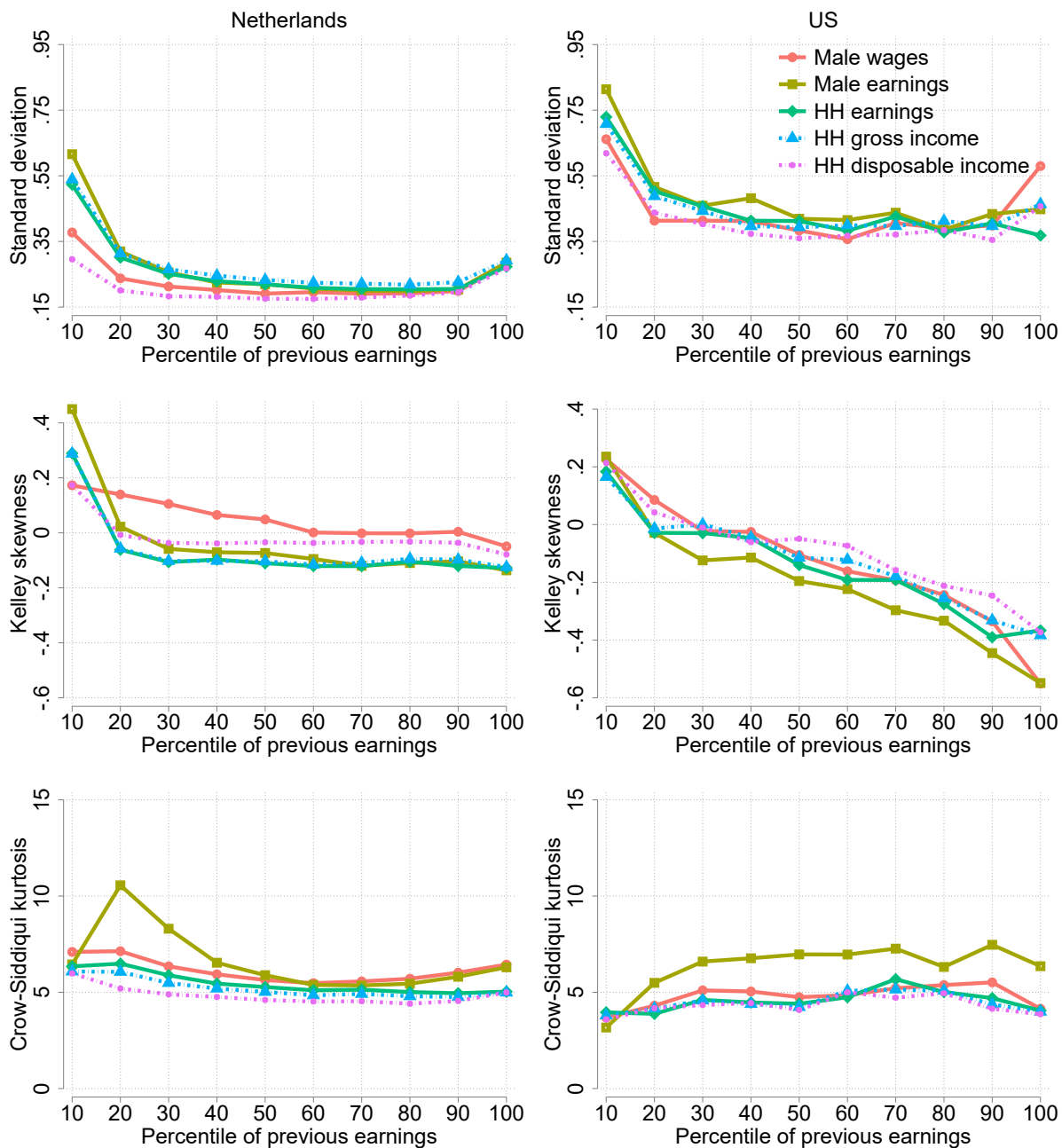


Figure 28: Netherlands, IPO after 2000 period (left), U.S., new PSID after 1997 period (right). Summary statistics of various income definitions, by previous earnings

D.2 Male earnings by recent earnings

Figures 29, 30, and 31 show the counterparts of Figures 1, 2, 6 and 8 with a different definition for the x-axis. Instead of using the percentile of last year's earnings, we use the percentile of *recent earnings*, following the definition in Guvenen et al. (2015). Namely, recent earnings are the average income of a worker between years $t - 1$ and $t - 5$ (after controlling for age and year effects). Additionally, and also following Guvenen et al. (2015), these figures require that information on earnings is available both in $t - 1$ and in two years between $t - 5$ and $t - 2$ to compute the measure of recent earnings. This contrasts with our main results, in which we just require information to be available in $t - 1$.

The different sample selection and quantile ranking implies a lower value for the standard deviation of earnings and a lower skewness (in absolute value), but all economic implications, both in the comparison of hours and wages and in the study of government insurance, remain unchanged.

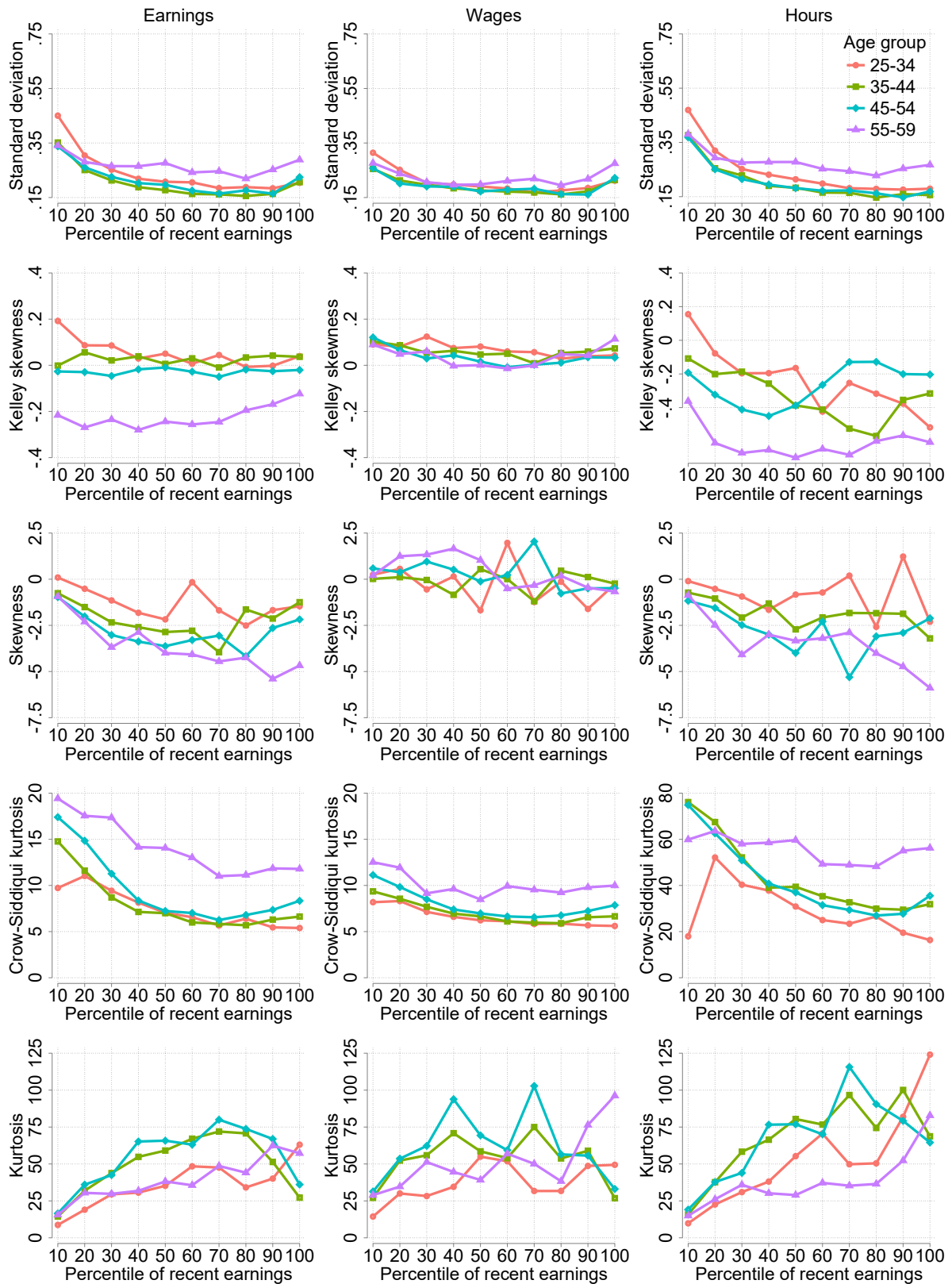


Figure 29: Netherlands: male earnings (left), male wages (middle), and male hours (right). Standard deviation (top row), Kelley skewness (second row), skewness (third row), Crow-Siddiqui kurtosis (fourth row), and kurtosis (bottom row). By recent earnings

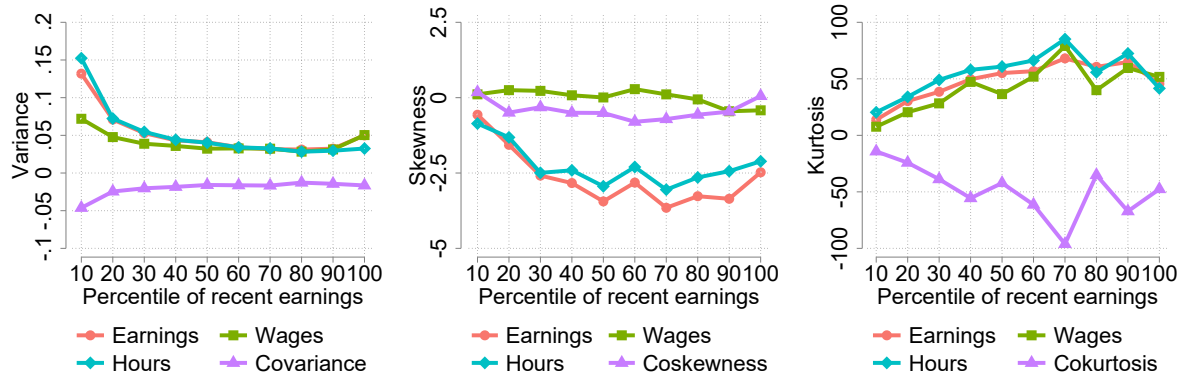


Figure 30: Netherlands: Decomposition of variance, skewness, and kurtosis of earnings. By recent earnings

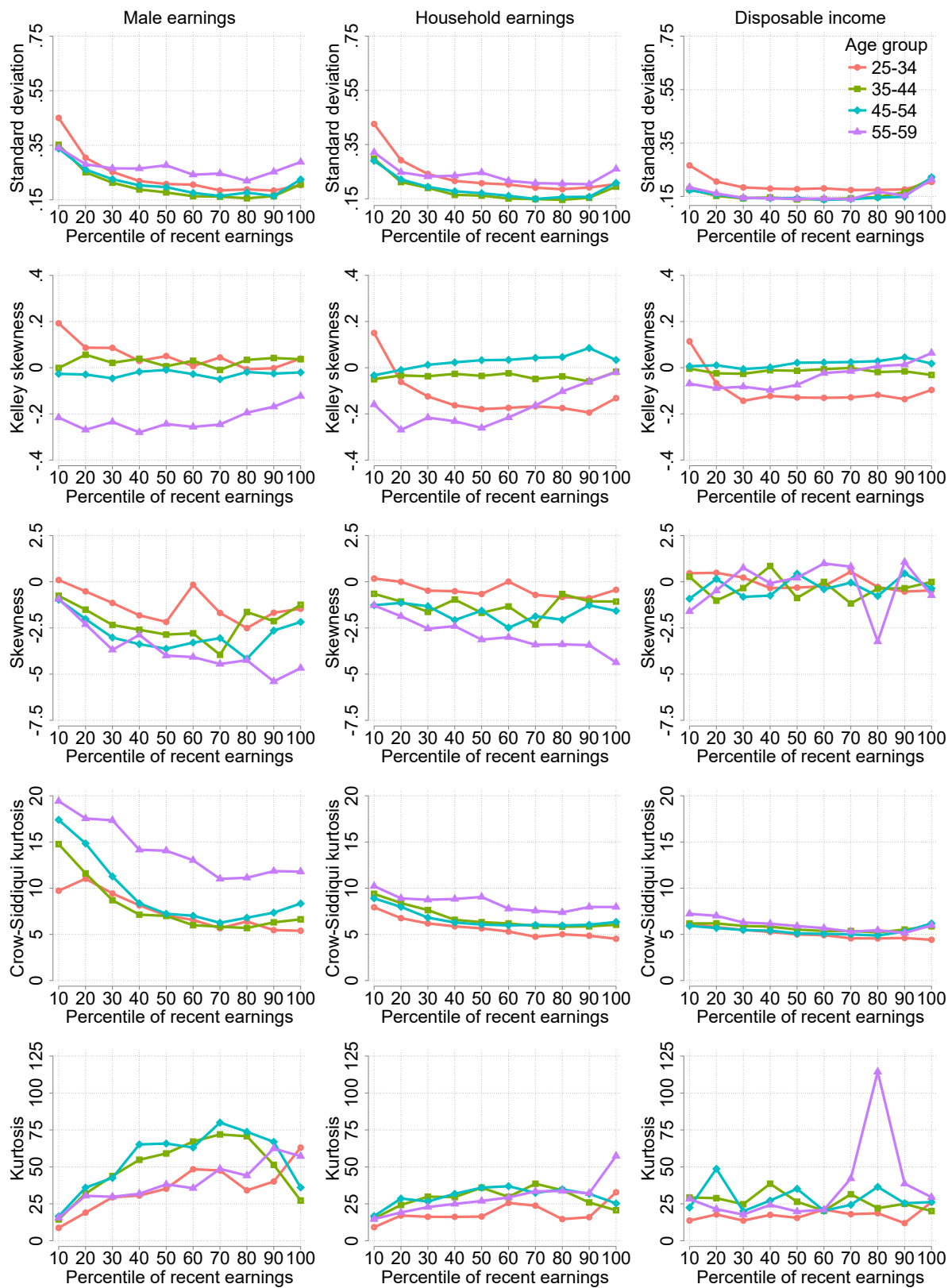


Figure 31: Netherlands: male earnings (left), household earnings (center), post-tax income (right). Standard deviation (top row), Kelley skewness (second row), skewness (third row), Crow-Siddiqui kurtosis (fourth row), and kurtosis (fifth row). By recent earnings

D.3 The role of asset income

Capital income consists of the following components: interests from saving accounts and bonds, dividends, the rental value of the residential property, income from other real estate, income from other assets, and mortgage interest payments. It does not include capital gains from stocks or other financial assets. The results hardly change with the inclusion of capital income, because capital income is relatively low compared with household labor income for the vast majority of the income distribution.

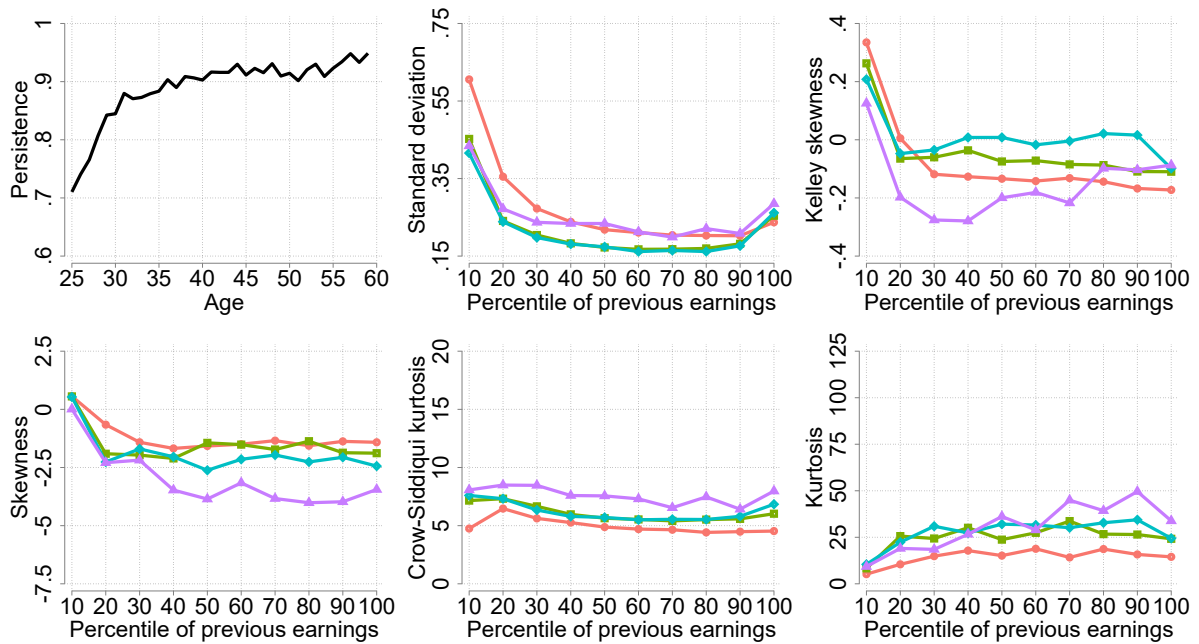


Figure 32: Netherlands: Household pre-tax income, including household earnings and capital income

D.4 Married or cohabiting couples only

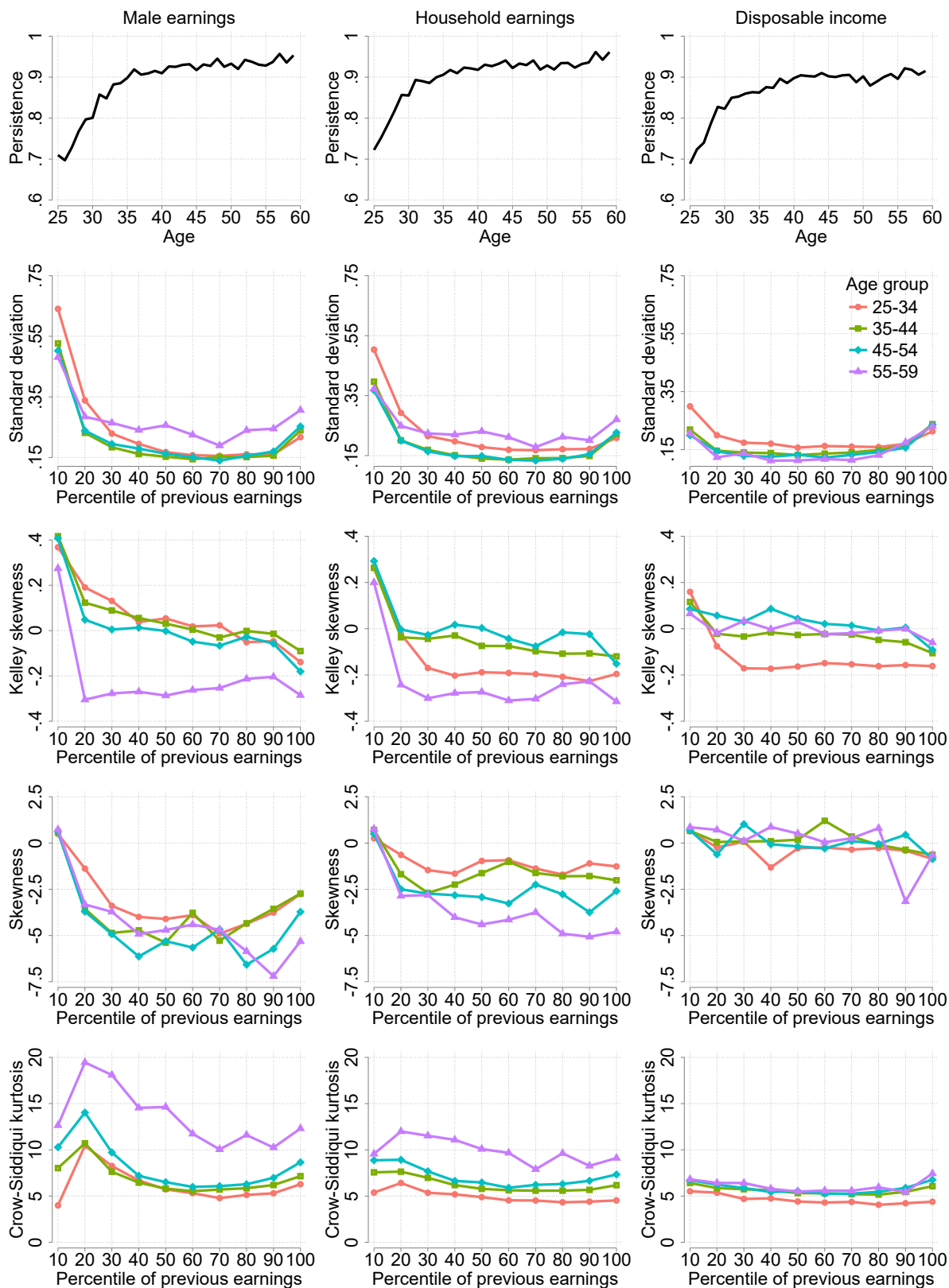


Figure 33: Netherlands: Male earnings (left), household earnings (center), post-tax income (right). Persistence (top row), standard deviation (second row), Kelley skewness (third row), skewness (fourth row), and Crow-Siddiqui kurtosis (bottom row). Married or cohabiting males

D.5 Family insurance, additional results

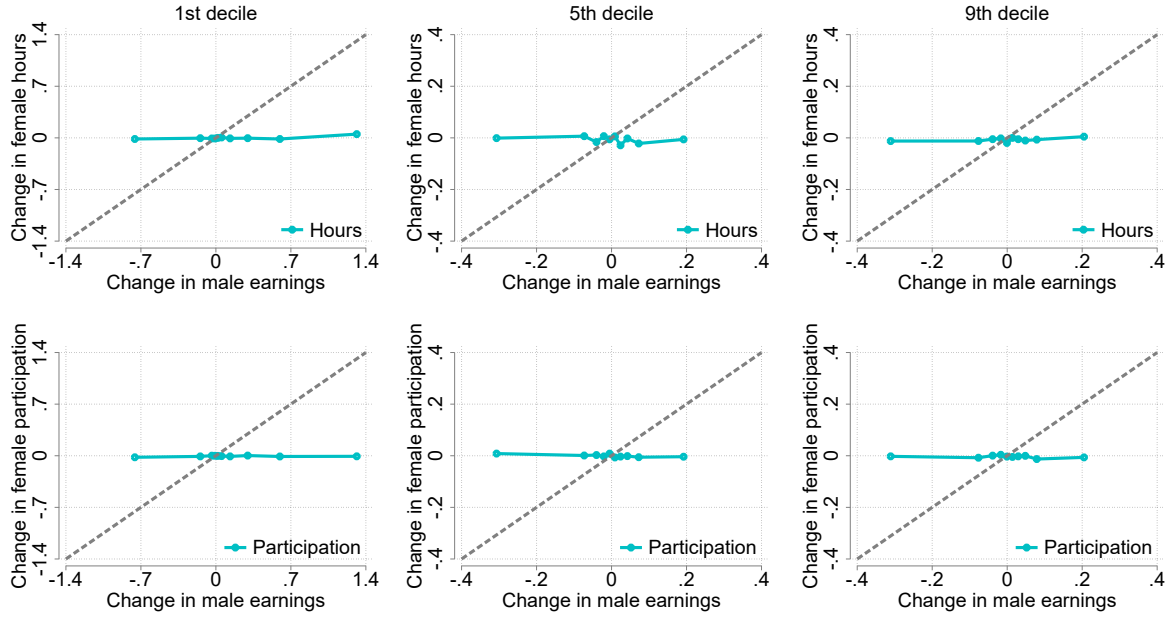


Figure 34: Netherlands: Male earnings changes and female labor supply. Each dot represents a decile of changes in male earnings. Lowest decile of previous male earnings (left), median decile of previous male earnings (center), 9th decile of previous male earnings (right). Top: one-year changes; bottom: changes in probability of labor market participation of the spouse over two years

D.6 Arc-percent measures

In Figure 35 we represent an alternative measure of annual earnings changes, namely arc-percent changes, defined as:

$$\Delta_{arc} Y_{t,t+1}^i = \frac{Y_{t+1}^i - Y_t^i}{(Y_{t+1}^i + Y_t^i)/2} \quad (3)$$

where Y_t^i is earnings in *levels*. Therefore, this measure (unlike log changes) does not require earnings in $t + 1$ to be above a minimum threshold and thus can accommodate possible zeros, which are particularly relevant when studying government insurance, since it can have a stronger effect for those individuals whose earnings change from being positive to being zero for one whole calendar year.

We observe a strong reduction in all arc-percent measures of earnings risk when we take into account government intervention, thus supporting the relevant role of the government in insuring workers against negative shocks, including the case in which earnings become zero.

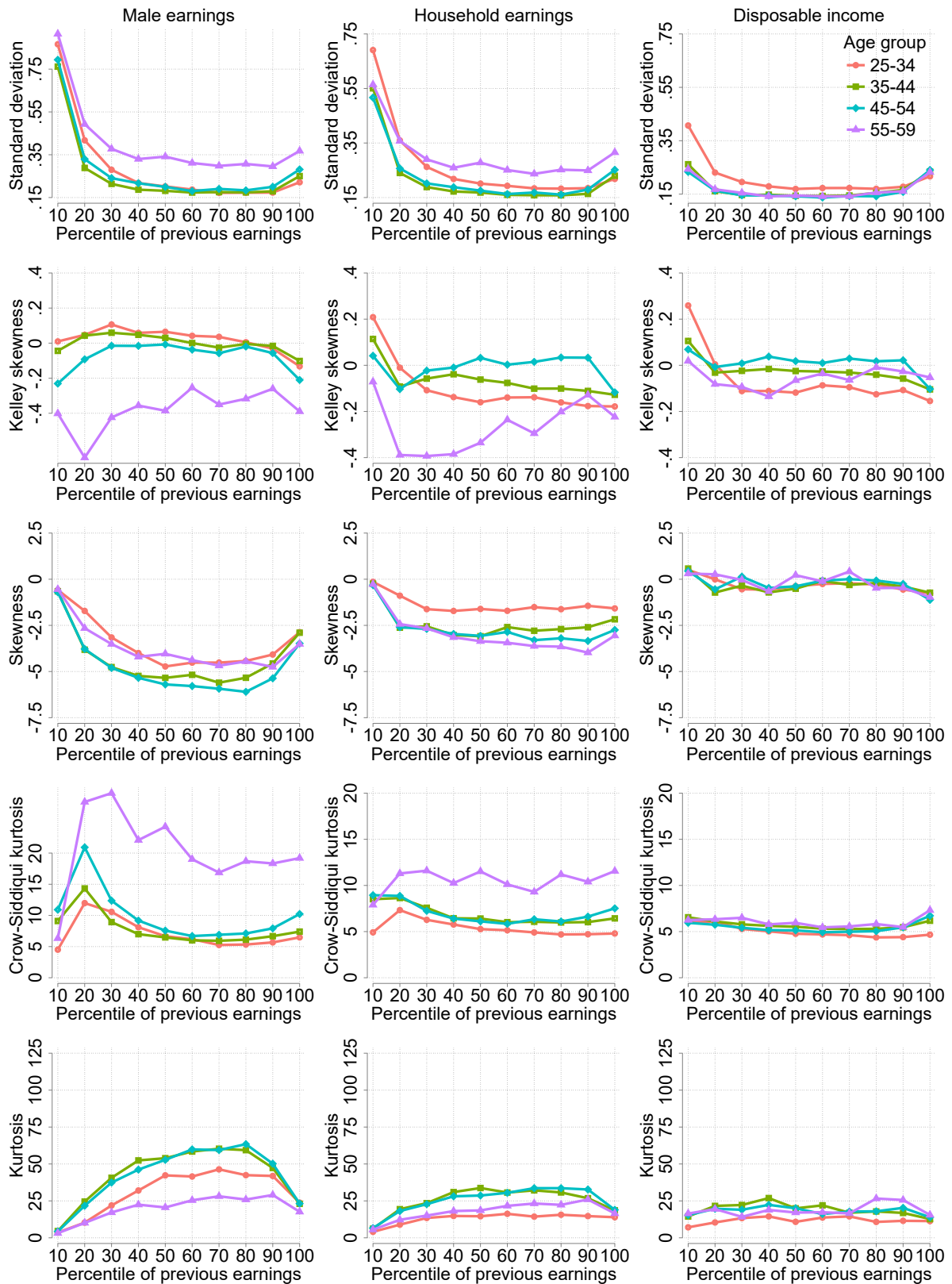


Figure 35: Netherlands: Male earnings (left), household earnings (center), post-tax income (right). Standard deviation (top row), Kelley skewness (second row), skewness (third row), Crow-Siddiqui kurtosis (fourth row) and kurtosis (fifth row). Arc percent

D.7 5-year changes

Figures 36 and 37 show the counterparts of Figures 1 and 8 for 5-year changes. We drop the 55-59 age group, as we do not observe 5-year variations for them inside our sample (25-60).

E Higher-order moments

E.1 Decomposing skewness and kurtosis

(Residual) log earnings are by definition the sum of log hours and log wages. Let Δy , Δh , and Δw denote the one-year change, respectively, in (log) earnings, hours, and wages. Dropping the household and time indices for simplicity, we can write

$$\Delta y = \Delta h + \Delta w$$

In Figure 2, we provide a standard variance decomposition of Δy at different points in the earnings distribution, using the fact that:

$$\sigma_{\Delta y}^2 = \sigma_{\Delta h}^2 + \sigma_{\Delta w}^2 + 2\text{cov}(\Delta h, \Delta w) \quad (4)$$

Let

$$\tilde{\mu}_z^k = E\left(\frac{z - \mu_z}{\sigma_z}\right)^k$$

denote the k -th standardized moment of a random variable z , where $\mu_z = Ez$ and $\sigma_z = \sqrt{E(z - \mu_z)^2}$.

Figure 6 performs a similar decomposition as the one in (4) for the third and fourth standardized moments—skewness and kurtosis—of earnings. The skewness of earnings satisfies

$$\begin{aligned} \tilde{\mu}_{\Delta y}^3 &= \frac{1}{\sigma_{\Delta y}^3} \left[E(\Delta h - \mu_{\Delta h})^3 + E(\Delta w - \mu_{\Delta w})^3 \right] + \text{co-sk}_{\Delta h, \Delta w} \\ &= \frac{1}{\sigma_{\Delta y}^3} \left[\sigma_{\Delta h}^3 \tilde{\mu}_{\Delta h}^3 + \sigma_{\Delta w}^3 \tilde{\mu}_{\Delta w}^3 \right] + \text{co-sk}_{\Delta h, \Delta w} \end{aligned}$$

where co-skewness is defined as

$$\text{co-sk}_{\Delta h, \Delta w} = 3 \frac{E[(\Delta h - \mu_{\Delta h})^2(\Delta w - \mu_{\Delta w})] + E[(\Delta h - \mu_{\Delta h})(\Delta w - \mu_{\Delta w})^2]}{\sigma_{\Delta y}^3}. \quad (5)$$

Following similar steps kurtosis, the fourth standardized moment, can be decomposed into

$$\tilde{\mu}_{\Delta y}^4 = \frac{1}{\sigma_{\Delta y}^4} \left[\sigma_{\Delta h}^4 \tilde{\mu}_{\Delta h}^4 + \sigma_{\Delta w}^4 \tilde{\mu}_{\Delta w}^4 \right] + \text{co-kt}_{\Delta h, \Delta w}$$

where co-kurtosis is defined as

$$\begin{aligned} \text{co-kt}_{\Delta h, \Delta w} = & \frac{4E[(\Delta h - \mu_{\Delta h})^3(\Delta w - \mu_{\Delta w})] + 4[(\Delta h - \mu_{\Delta h})(\Delta w - \mu_{\Delta w})^3]}{\sigma_{\Delta y}^4} \\ & + \frac{6E[(\Delta h - \mu_{\Delta h})^2(\Delta w - \mu_{\Delta w})^2]}{\sigma_{\Delta y}^4}. \end{aligned} \quad (6)$$

We denote the elements in the decomposition of skewness, respectively, the contribution of hours to the skewness, the contribution of wages to the skewness, and the co-skewness. Similarly, we denote the first two elements in the decomposition of kurtosis the contribution of hours and wages to kurtosis, whilst the two addenda in the bottom two rows jointly form the co-kurtosis.

The contributions of hours and wages to both skewness and kurtosis follows naturally from their respective definitions. For instance, *ceteris paribus*, a more left-skewed distribution of wage changes will lead to a more left-skewed distribution of earnings changes.

Co-skewness is more positive whenever large changes in hours are associated with positive changes in wages, and large changes in wages are associated with positive changes in hours. Intuitively, even if both the distributions of hours and wage changes were symmetric, if it were the case that when hours change a lot wages increase, the resulting distribution of earnings changes would be positively skewed (large positive earnings shocks become more likely than large negative earnings shocks).

Co-kurtosis is composed of three elements. It is more positive whenever (1) large absolute changes in hours are associated with changes in wages of the same sign, (2) large absolute in wages are associated with changes in hours of the same sign, and (3) large absolute changes in hours and wages happen at the same time. If, as is in the case in our main sample, tail events in wages (hours) are associated with changes in hours (wages) of the opposite sign, co-kurtosis can be negative.

E.2 Kurtosis: fourth standardized moment

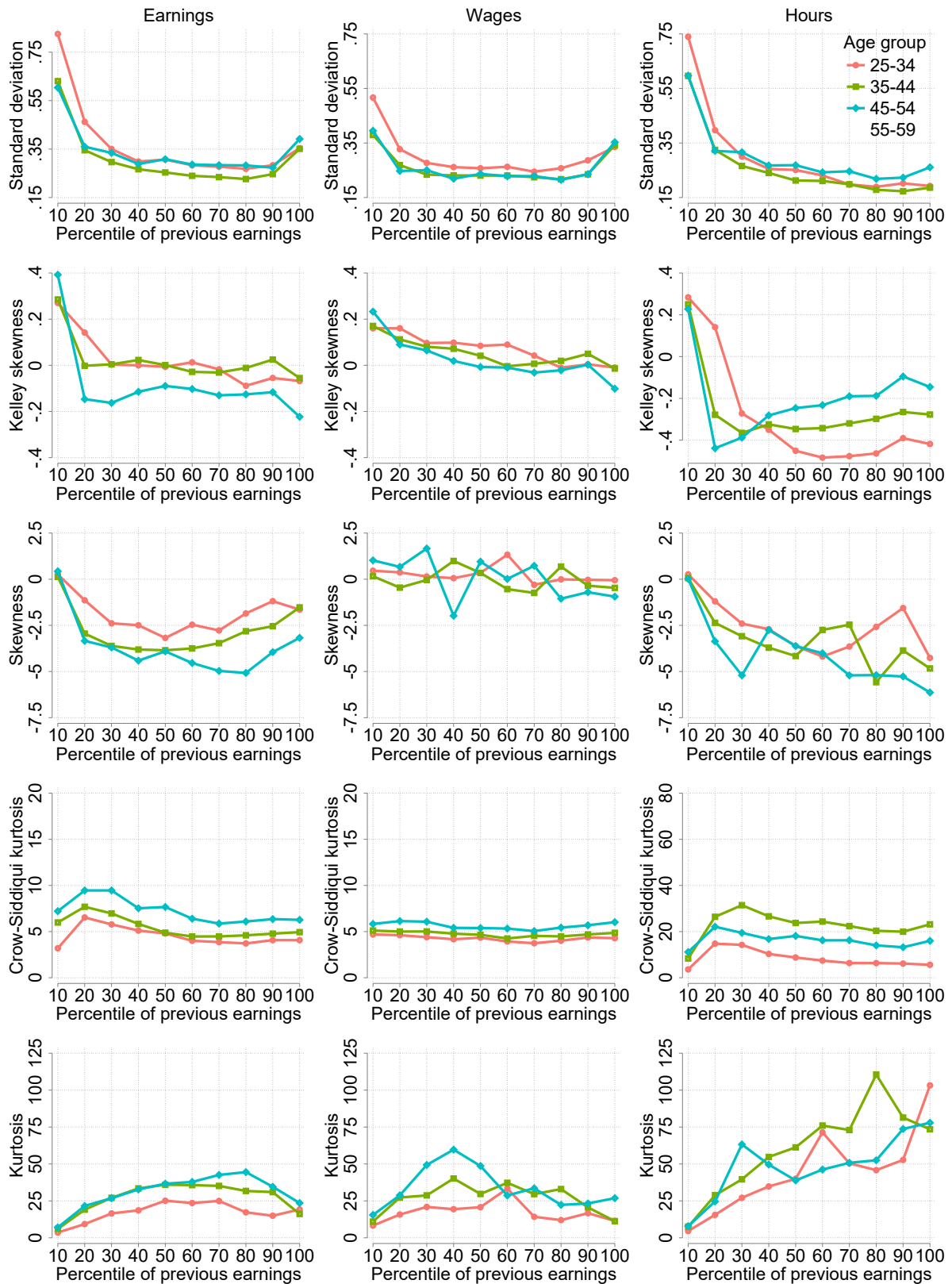


Figure 36: Netherlands: male earnings (left), male wages (middle), and male hours (right). Standard deviation (top row), Kelley skewness (second row), skewness (third row), Crow-Siddiqui kurtosis (fourth row), and kurtosis (bottom row). 5-year changes

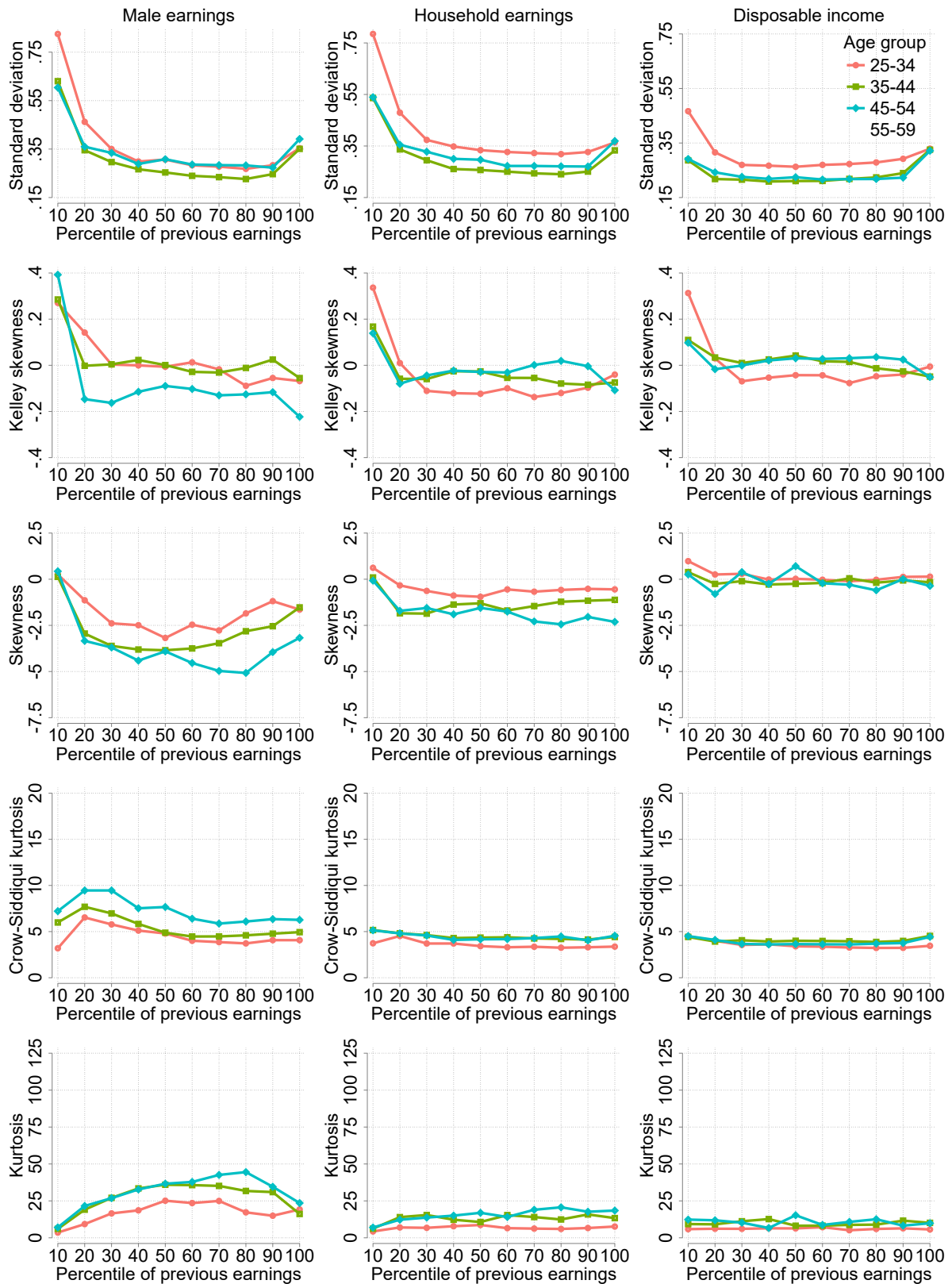


Figure 37: Netherlands: Male earnings (left), household earnings (center), post-tax income (right). Standard deviation (top row), Kelley skewness (second row), skewness (third row), Crow-Siddiqui kurtosis (fourth row), and kurtosis (fifth row). 5-year changes

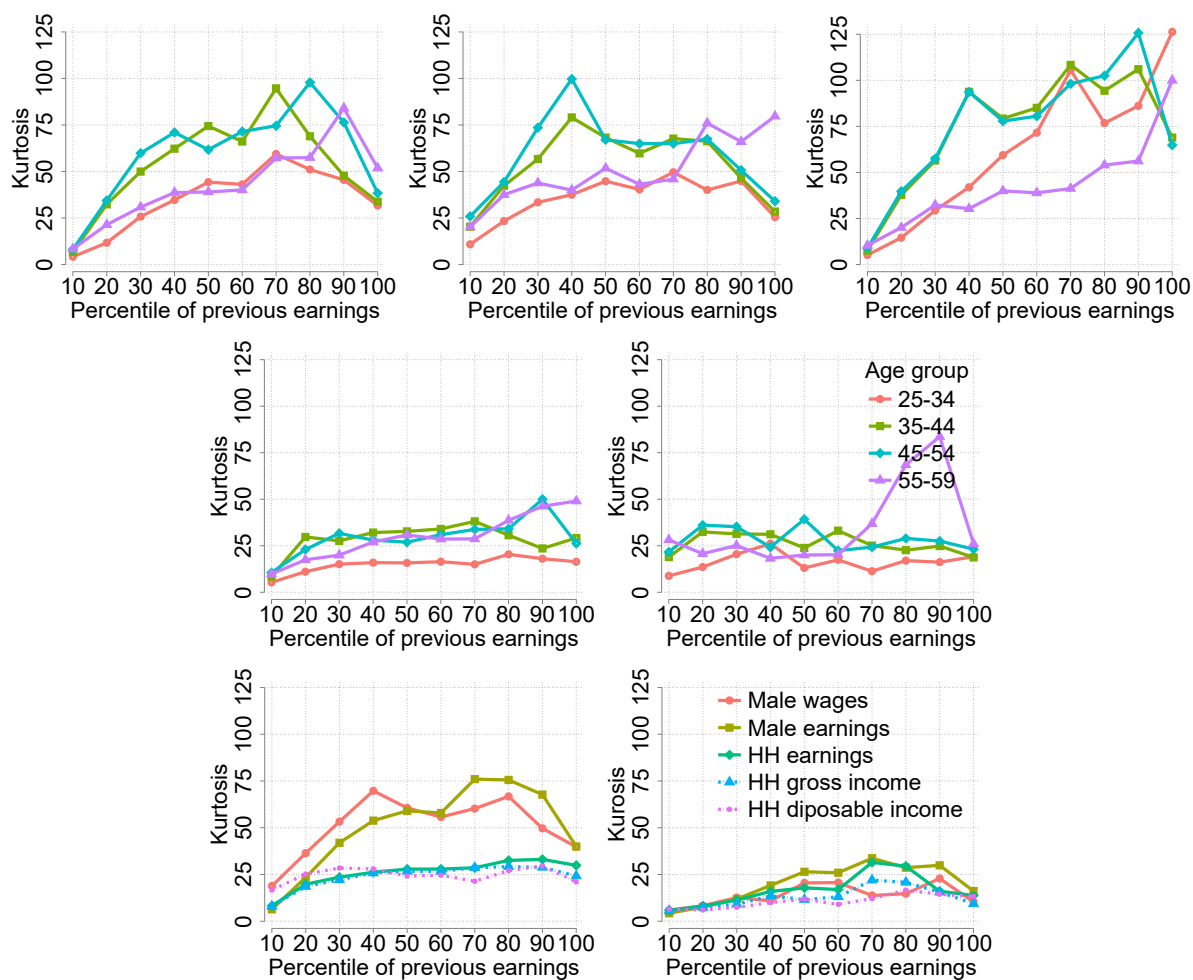


Figure 38: Pearson's measures of Kurtosis: Dutch male earnings (top left), Dutch male wages (top center), Dutch male hours (top right), Dutch pre-tax household income (middle left), Dutch after-tax household income (middle right), NL combined income measures (bottom left), US combined income measures (bottom right)