# ONLINE APPENDIX to "Income Risk Inequality: Evidence from Spanish Administrative Records"

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**Abstract**

This appendix provides additional results the complement the paper and the main appendix. In Online Appendix S-A, we report additional results relating to Section 3 of the paper. In Online Appendix S-B we detail the calculations of the welfare cost of risk. In Online Appendix S-C we report the coefficients in the Poisson regressions used in the CV measure in Sections 4 and 5 in the paper. In Online Appendix S-D we show how we account for unobserved heterogeneity. In Online Appendix S-E we provide details about quantile estimation. In Online Appendix S-F we describe how we estimate subjective income expectations. Lastly, in Online Appendix S-G we report additional results regarding the robustness checks performed in the paper.

# S-A Additional tables and figures on income inequality and dynamics

Table S-A1: Descriptive statistics for the CS sample

(a) Panel A: Basic summary statistics

| Year | Obs | Mean Income | | Females | Age Shares % | | | Education Shares % | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (×1000) | Males | Females | % Share | [25,35] | [36,45] | [46,55] | Primary | Lower Sec | Upper Sec | College |
| 2005 | 415 | 30064 | 21363 | 43.8 | 44.6 | 33.3 | 22.1 | 14.5 | 36.5 | 28.2 | 20.7 |
| 2006 | 435 | 30532 | 21863 | 44.3 | 43.6 | 33.7 | 22.7 | 14.3 | 36.6 | 27.8 | 21.3 |
| 2007 | 455 | 30905 | 22400 | 44.8 | 42.8 | 34.1 | 23.1 | 14.1 | 36.7 | 27.5 | 21.6 |
| 2008 | 463 | 30786 | 22788 | 45.6 | 41.6 | 34.6 | 23.8 | 13.7 | 36.6 | 27.4 | 22.3 |
| 2009 | 444 | 30676 | 23347 | 46.3 | 39.7 | 35.4 | 25.0 | 12.7 | 36.3 | 27.6 | 23.5 |
| 2010 | 433 | 30094 | 22916 | 46.8 | 38.0 | 36.1 | 25.9 | 12.1 | 36.4 | 27.5 | 24.1 |
| 2011 | 425 | 29280 | 22132 | 47.3 | 36.4 | 36.9 | 26.8 | 11.6 | 36.4 | 27.4 | 24.6 |
| 2012 | 407 | 28140 | 21387 | 47.6 | 34.5 | 37.8 | 27.7 | 11.1 | 35.8 | 27.6 | 25.6 |
| 2013 | 396 | 27294 | 21141 | 47.5 | 32.7 | 38.6 | 28.7 | 11.1 | 35.8 | 27.2 | 25.9 |
| 2014 | 397 | 27087 | 21209 | 47.3 | 31.4 | 39.0 | 29.5 | 11.2 | 35.9 | 26.8 | 26.1 |
| 2015 | 405 | 27605 | 21650 | 47.4 | 30.3 | 39.2 | 30.5 | 11.2 | 35.9 | 26.5 | 26.4 |
| 2016 | 409 | 28119 | 22153 | 47.4 | 29.5 | 39.1 | 31.4 | 11.1 | 35.7 | 26.3 | 26.8 |
| 2017 | 415 | 28153 | 22174 | 47.5 | 29.0 | 38.7 | 32.3 | 11.1 | 35.6 | 26.1 | 27.2 |
| 2018 | 420 | 28504 | 22479 | 47.6 | 28.7 | 37.9 | 33.4 | 11.0 | 35.4 | 26.1 | 27.6 |

(b) Panel B: Percentiles of annual earnings

| Year | P1 | P5 | P10 | P25 | P50 | P75 | P90 | P95 | P99 | P99.5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2005 | 1866 | 4166 | 6972 | 13860 | 21235 | 31997 | 47977 | 62769 | 106369 | 133741 |
| 2006 | 1940 | 4455 | 7426 | 14360 | 21596 | 32453 | 48514 | 63223 | 106207 | 133169 |
| 2007 | 1990 | 4562 | 7616 | 14580 | 21867 | 32889 | 49210 | 63959 | 108446 | 136093 |
| 2008 | 1969 | 4357 | 7184 | 14101 | 21981 | 33179 | 49809 | 64652 | 109276 | 136193 |
| 2009 | 1887 | 3786 | 6285 | 13411 | 22150 | 33876 | 51115 | 65667 | 111121 | 137111 |
| 2010 | 1869 | 3695 | 6082 | 13044 | 21788 | 33330 | 50055 | 64478 | 109173 | 134855 |
| 2011 | 1827 | 3568 | 5864 | 12488 | 21217 | 32283 | 48434 | 62656 | 105661 | 131472 |
| 2012 | 1719 | 3260 | 5396 | 11837 | 20509 | 31093 | 46591 | 60896 | 101702 | 127134 |
| 2013 | 1661 | 2988 | 4864 | 10976 | 19965 | 30737 | 46361 | 60020 | 99412 | 125199 |
| 2014 | 1684 | 3039 | 4929 | 10897 | 19847 | 30712 | 46202 | 59883 | 100242 | 126201 |
| 2015 | 1736 | 3253 | 5306 | 11337 | 20031 | 31056 | 47057 | 60888 | 103314 | 130508 |
| 2016 | 1804 | 3567 | 5811 | 12043 | 20448 | 31465 | 47567 | 61494 | 104497 | 132484 |
| 2017 | 1962 | 3855 | 6239 | 12520 | 20465 | 31277 | 47052 | 60913 | 103168 | 130550 |
| 2018 | 2026 | 4119 | 6691 | 13050 | 20802 | 31492 | 46947 | 60816 | 103516 | 130403 |

*Notes: CS sample. Annual earnings are reported in 2018 U.S. dollars.*

Table S-A2: Descriptive statistics for the LS sample

(a) Panel A: Basic summary statistics

| Year | Obs | Mean Income | | Females | Age Shares % | | | Education Shares % | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (×1000) | Males | Females | % Share | [25,35] | [36,45] | [46,55] | Primary | Lower Sec | Upper Sec | College |
| 2005 | 283 | 31215 | 22935 | 44.1 | 47.9 | 37.5 | 14.6 | 10.9 | 35.7 | 29.9 | 23.6 |
| 2006 | 289 | 31945 | 23353 | 45.1 | 47.2 | 37.9 | 14.9 | 10.3 | 35.8 | 29.5 | 24.3 |
| 2007 | 292 | 33129 | 24397 | 46.1 | 46.4 | 38.5 | 15.1 | 9.9 | 35.3 | 29.5 | 25.4 |
| 2008 | 286 | 33606 | 25140 | 46.9 | 44.9 | 39.5 | 15.6 | 9.4 | 35.1 | 29.3 | 26.2 |
| 2009 | 281 | 32824 | 25411 | 47.3 | 43.1 | 40.6 | 16.3 | 9.1 | 35.2 | 29.0 | 26.7 |
| 2010 | 281 | 31682 | 24729 | 47.6 | 41.6 | 41.5 | 16.9 | 9.0 | 35.3 | 28.7 | 27.0 |
| 2011 | 279 | 30873 | 23991 | 48.0 | 39.8 | 42.7 | 17.4 | 8.8 | 35.0 | 28.5 | 27.6 |
| 2012 | 273 | 29345 | 22943 | 48.2 | 37.7 | 44.1 | 18.2 | 8.7 | 34.6 | 28.4 | 28.3 |
| 2013 | 273 | 28088 | 22382 | 48.0 | 36.0 | 45.2 | 18.9 | 8.9 | 34.7 | 27.9 | 28.5 |

(b) Panel B: Percentiles of annual earnings

| Year | P1 | P5 | P10 | P25 | P50 | P75 | P90 | P95 | P99 | P99.5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2005 | 2300 | 5677 | 8991 | 15835 | 22485 | 33471 | 48942 | 63131 | 104378 | 129582 |
| 2006 | 2456 | 6139 | 9537 | 16284 | 22988 | 33946 | 49398 | 63505 | 104070 | 129506 |
| 2007 | 2618 | 6690 | 10197 | 16898 | 23775 | 35213 | 51118 | 65830 | 108241 | 134470 |
| 2008 | 2711 | 6743 | 10203 | 17024 | 24324 | 36021 | 52166 | 66908 | 109279 | 135642 |
| 2009 | 2366 | 5591 | 9037 | 16407 | 24273 | 36148 | 52437 | 66492 | 109634 | 133683 |
| 2010 | 2263 | 5269 | 8505 | 15766 | 23617 | 35180 | 50875 | 64633 | 106835 | 129671 |
| 2011 | 2233 | 5160 | 8221 | 15245 | 23013 | 34199 | 49275 | 62837 | 103309 | 126178 |
| 2012 | 2000 | 4498 | 7399 | 14314 | 21961 | 32597 | 47140 | 60655 | 98747 | 121339 |
| 2013 | 1838 | 3881 | 6424 | 13116 | 21239 | 31951 | 46508 | 59414 | 95969 | 117924 |

*Notes: LS sample, restricted to non-missing 1-year and 5-year changes in log earnings. Annual earnings are reported in 2018 U.S. dollars.*

Table S-A3: Descriptive statistics for the H sample

(a) Panel A: Basic summary statistics

| Year | Obs | Mean Income | | Females | Age Shares % | | | Education Shares % | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (×1000) | Males | Females | % Share | [25,35] | [36,45] | [46,55] | Primary | Lower Sec | Upper Sec | College |
| 2008 | 240 | 35505 | 27001 | 45.8 | 40.1 | 42.8 | 17.2 | 8.8 | 34.8 | 30.4 | 26.0 |
| 2009 | 242 | 34563 | 27082 | 46.5 | 38.7 | 43.6 | 17.7 | 8.6 | 34.7 | 30.0 | 26.7 |
| 2010 | 245 | 33390 | 26244 | 47.2 | 37.4 | 44.4 | 18.2 | 8.4 | 34.8 | 29.6 | 27.1 |
| 2011 | 244 | 32652 | 25483 | 47.7 | 35.6 | 45.5 | 18.9 | 8.2 | 34.5 | 29.5 | 27.8 |
| 2012 | 239 | 30914 | 24165 | 48.1 | 33.6 | 46.7 | 19.6 | 8.1 | 34.3 | 29.2 | 28.4 |
| 2013 | 238 | 30025 | 23815 | 48.1 | 31.9 | 47.8 | 20.3 | 8.0 | 34.2 | 28.9 | 28.9 |

(b) Panel B: Percentiles of annual earnings

| Year | P1 | P5 | P10 | P25 | P50 | P75 | P90 | P95 | P99 | P99.5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2008 | 3617 | 8556 | 12165 | 18571 | 25968 | 38213 | 54649 | 70024 | 113555 | 140634 |
| 2009 | 2844 | 7111 | 10741 | 17974 | 25788 | 38146 | 54522 | 69248 | 112818 | 137418 |
| 2010 | 2726 | 6648 | 10168 | 17382 | 25040 | 36971 | 52759 | 67078 | 109410 | 132854 |
| 2011 | 2724 | 6619 | 9948 | 16931 | 24430 | 35915 | 51096 | 65213 | 105915 | 129546 |
| 2012 | 2406 | 5840 | 9075 | 15974 | 23155 | 33922 | 48566 | 62297 | 100849 | 123337 |
| 2013 | 2217 | 5204 | 8317 | 15096 | 22628 | 33601 | 48233 | 61422 | 98156 | 121750 |

*Notes: H sample, restricted to non-missing 1-year and 5-year changes in log earnings. Annual earnings are reported in 2018 U.S. dollars.*

Table S-A4: Descriptive statistics for the B sample

(a) Panel A: Basic summary statistics

| Year | Obs | Mean Income | Age Shares % | | | Education Shares % | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (×1000) | Males | [25,35] | [36,45] | [46,55] | Primary | Lower Sec | Upper Sec | College |
| 2006 | 223.091 | 32112 | 41.0 | 34.5 | 24.6 | 17.7 | 40.0 | 26.5 | 15.8 |
| 2007 | 233.686 | 32131 | 40.3 | 34.6 | 25.1 | 17.3 | 40.0 | 26.3 | 16.3 |
| 2008 | 244.511 | 31391 | 40.0 | 34.7 | 25.3 | 17.3 | 40.1 | 26.0 | 16.6 |
| 2009 | 249.983 | 30035 | 38.9 | 35.1 | 26.0 | 17.0 | 40.0 | 25.9 | 17.0 |
| 2010 | 254.180 | 28484 | 37.7 | 35.5 | 26.8 | 16.8 | 40.2 | 25.7 | 17.3 |
| 2011 | 253.227 | 27125 | 36.2 | 36.1 | 27.7 | 16.5 | 40.5 | 25.5 | 17.6 |
| 2012 | 250.995 | 25070 | 34.4 | 36.9 | 28.7 | 16.3 | 40.6 | 25.3 | 17.8 |
| 2013 | 247.411 | 24227 | 32.4 | 37.6 | 29.9 | 16.2 | 40.7 | 25.2 | 17.9 |
| 2014 | 242.084 | 24497 | 30.6 | 38.3 | 31.1 | 16.1 | 40.7 | 25.0 | 18.2 |
| 2015 | 235.009 | 25784 | 29.1 | 38.7 | 32.2 | 15.8 | 40.8 | 24.9 | 18.5 |
| 2016 | 229.111 | 26906 | 27.7 | 39.1 | 33.2 | 15.4 | 40.9 | 24.8 | 18.9 |
| 2017 | 225.461 | 27476 | 26.8 | 39.0 | 34.2 | 15.0 | 40.8 | 24.8 | 19.4 |
| 2018 | 222.442 | 28281 | 26.4 | 38.7 | 35.0 | 14.7 | 40.7 | 24.8 | 19.7 |

(b) Panel B: Percentiles of annual earnings

| Year | P1 | P5 | P10 | P25 | P50 | P75 | P90 | P95 | P99 | P99.5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2006 | 0 | 6348 | 11950 | 18743 | 25032 | 37797 | 56784 | 74954 | 130901 | 168982 |
| 2007 | 0 | 3597 | 10834 | 18641 | 25187 | 38030 | 57152 | 75835 | 133075 | 170806 |
| 2008 | 0 | 1927 | 9019 | 18064 | 24881 | 37535 | 56419 | 74316 | 131104 | 166656 |
| 2009 | 0 | 0 | 6171 | 15999 | 24017 | 36692 | 55767 | 73403 | 129605 | 163291 |
| 2010 | 0 | 0 | 4756 | 13936 | 23024 | 35321 | 53682 | 70646 | 125337 | 159883 |
| 2011 | 0 | 0 | 2832 | 12210 | 22175 | 34055 | 51790 | 68500 | 121018 | 154562 |
| 2012 | 0 | 0 | 945 | 9812 | 20811 | 32009 | 48786 | 64957 | 113658 | 144361 |
| 2013 | 0 | 0 | 387 | 8207 | 19997 | 31455 | 48566 | 64027 | 110961 | 140965 |
| 2014 | 0 | 0 | 814 | 8556 | 20218 | 31774 | 48908 | 64455 | 112566 | 143896 |
| 2015 | 0 | 0 | 2016 | 10334 | 21073 | 32726 | 50304 | 66336 | 117219 | 150881 |
| 2016 | 0 | 0 | 3012 | 12294 | 21943 | 33682 | 51453 | 67728 | 120707 | 155770 |
| 2017 | 0 | 58 | 4333 | 13951 | 22307 | 33927 | 51268 | 67301 | 120179 | 154609 |
| 2018 | 0 | 824 | 5636 | 15252 | 22900 | 34367 | 51461 | 67515 | 120712 | 156436 |

*Notes: B sample. Annual earnings are reported in 2018 U.S. dollars. Only males.*

Table S-A5: Descriptive statistics for the B sample, with positive income

(a) Panel A: Basic summary statistics

| Year | Obs | Mean Income | Age Shares % | | | Education Shares % | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (×1000) | Males | [25,35] | [36,45] | [46,55] | Primary | Lower Sec | Upper Sec | College |
| 2006 | 218.712 | 27711 | 40.9 | 34.5 | 24.6 | 17.6 | 40.0 | 26.6 | 15.8 |
| 2007 | 226.159 | 28087 | 40.2 | 34.7 | 25.1 | 17.1 | 40.2 | 26.4 | 16.4 |
| 2008 | 235.093 | 27620 | 39.8 | 34.8 | 25.4 | 17.0 | 40.2 | 26.1 | 16.7 |
| 2009 | 236.784 | 26826 | 38.4 | 35.3 | 26.3 | 16.5 | 40.1 | 26.1 | 17.3 |
| 2010 | 239.605 | 25564 | 37.2 | 35.7 | 27.1 | 16.3 | 40.4 | 25.8 | 17.6 |
| 2011 | 236.440 | 24577 | 35.6 | 36.2 | 28.2 | 15.8 | 40.6 | 25.7 | 17.9 |
| 2012 | 229.793 | 23167 | 33.5 | 36.8 | 29.6 | 15.4 | 40.5 | 25.8 | 18.3 |
| 2013 | 224.752 | 22563 | 31.6 | 37.5 | 30.9 | 15.1 | 40.7 | 25.7 | 18.5 |
| 2014 | 221.923 | 22607 | 30.1 | 38.2 | 31.7 | 15.2 | 40.8 | 25.4 | 18.7 |
| 2015 | 219.181 | 23388 | 28.7 | 38.8 | 32.4 | 15.0 | 40.9 | 25.2 | 18.9 |
| 2016 | 215.660 | 24183 | 27.5 | 39.2 | 33.2 | 14.7 | 40.9 | 25.1 | 19.2 |
| 2017 | 214.367 | 24448 | 26.7 | 39.1 | 34.2 | 14.5 | 40.8 | 25.1 | 19.6 |
| 2018 | 213.275 | 24954 | 26.3 | 38.8 | 34.9 | 14.2 | 40.7 | 25.1 | 20.0 |

(b) Panel B: Percentiles of annual earnings

| Year | P1 | P5 | P10 | P25 | P50 | P75 | P90 | P95 | P99 | P99.5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2006 | 1987 | 7403 | 11279 | 16162 | 21459 | 32301 | 48462 | 63857 | 111662 | 143935 |
| 2007 | 1644 | 7194 | 11285 | 16297 | 21779 | 32723 | 49028 | 64957 | 114061 | 145903 |
| 2008 | 1363 | 6242 | 10351 | 16010 | 21597 | 32416 | 48457 | 63754 | 112489 | 142797 |
| 2009 | 1047 | 5228 | 8377 | 14860 | 21097 | 31980 | 48220 | 63369 | 111545 | 140805 |
| 2010 | 1026 | 4402 | 6465 | 13631 | 20268 | 30855 | 46441 | 61151 | 107852 | 138024 |
| 2011 | 621 | 3280 | 5458 | 12701 | 19661 | 29917 | 45042 | 59569 | 104753 | 134212 |
| 2012 | 444 | 2664 | 5136 | 11486 | 18737 | 28388 | 42760 | 56862 | 99211 | 126801 |
| 2013 | 359 | 2335 | 4627 | 10309 | 18208 | 28116 | 42636 | 56154 | 97214 | 123367 |
| 2014 | 344 | 2184 | 4422 | 10157 | 18277 | 28228 | 42866 | 56400 | 98274 | 125706 |
| 2015 | 433 | 2466 | 4730 | 11140 | 18738 | 28809 | 43781 | 57660 | 101636 | 131751 |
| 2016 | 500 | 2852 | 5299 | 12401 | 19347 | 29465 | 44567 | 58613 | 104174 | 134866 |
| 2017 | 633 | 3445 | 6169 | 13222 | 19507 | 29513 | 44273 | 58038 | 103296 | 132568 |
| 2018 | 773 | 4052 | 7240 | 13949 | 19895 | 29760 | 44257 | 58048 | 103687 | 134422 |

*Notes: B sample, positive income. Annual earnings are reported in 2018 euros. Only males.*

Table S-A6: Descriptive statistics for the B sample, with positive income

(a) Panel A: Basic summary statistics

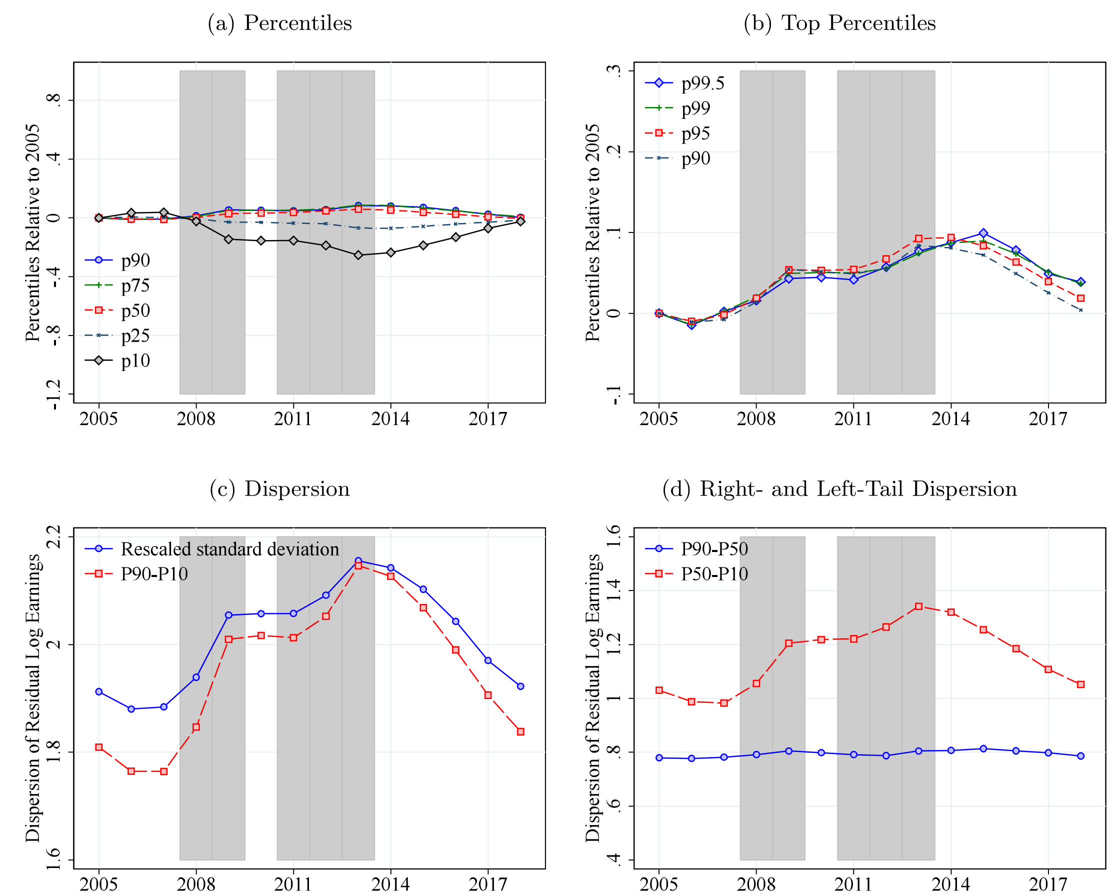
| Year | Obs | Mean Income | Age Shares % | | | Education Shares % | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (×1000) | Males | [25,35] | [36,45] | [46,55] | Primary | Lower Sec | Upper Sec | College |
| 2006 | 218.712 | 32755 | 40.9 | 34.5 | 24.6 | 17.6 | 40.0 | 26.6 | 15.8 |
| 2007 | 226.159 | 33200 | 40.2 | 34.7 | 25.1 | 17.1 | 40.2 | 26.4 | 16.4 |
| 2008 | 235.093 | 32648 | 39.8 | 34.8 | 25.4 | 17.0 | 40.2 | 26.1 | 16.7 |
| 2009 | 236.784 | 31709 | 38.4 | 35.3 | 26.3 | 16.5 | 40.1 | 26.1 | 17.3 |
| 2010 | 239.605 | 30217 | 37.2 | 35.7 | 27.1 | 16.3 | 40.4 | 25.8 | 17.6 |
| 2011 | 236.440 | 29051 | 35.6 | 36.2 | 28.2 | 15.8 | 40.6 | 25.7 | 17.9 |
| 2012 | 229.793 | 27384 | 33.5 | 36.8 | 29.6 | 15.4 | 40.5 | 25.8 | 18.3 |
| 2013 | 224.752 | 26670 | 31.6 | 37.5 | 30.9 | 15.1 | 40.7 | 25.7 | 18.5 |
| 2014 | 221.923 | 26723 | 30.1 | 38.2 | 31.7 | 15.2 | 40.8 | 25.4 | 18.7 |
| 2015 | 219.181 | 27646 | 28.7 | 38.8 | 32.4 | 15.0 | 40.9 | 25.2 | 18.9 |
| 2016 | 215.660 | 28585 | 27.5 | 39.2 | 33.2 | 14.7 | 40.9 | 25.1 | 19.2 |
| 2017 | 214.367 | 28898 | 26.7 | 39.1 | 34.2 | 14.5 | 40.8 | 25.1 | 19.6 |
| 2018 | 213.275 | 29496 | 26.3 | 38.8 | 34.9 | 14.2 | 40.7 | 25.1 | 20.0 |

(b) Panel B: Percentiles of annual earnings

| Year | P1 | P5 | P10 | P25 | P50 | P75 | P90 | P95 | P99 | P99.5 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2006 | 2348 | 8750 | 13332 | 19104 | 25365 | 38181 | 57284 | 75481 | 131989 | 170135 |
| 2007 | 1944 | 8503 | 13339 | 19264 | 25743 | 38680 | 57953 | 76781 | 134824 | 172463 |
| 2008 | 1612 | 7378 | 12236 | 18924 | 25529 | 38316 | 57277 | 75359 | 132966 | 168791 |
| 2009 | 1238 | 6180 | 9902 | 17565 | 24937 | 37801 | 56998 | 74904 | 131850 | 166437 |
| 2010 | 1213 | 5203 | 7642 | 16112 | 23957 | 36472 | 54895 | 72283 | 127485 | 163148 |
| 2011 | 734 | 3877 | 6452 | 15013 | 23240 | 35363 | 53241 | 70412 | 123822 | 158644 |
| 2012 | 525 | 3149 | 6071 | 13576 | 22147 | 33555 | 50543 | 67213 | 117270 | 149883 |
| 2013 | 424 | 2760 | 5469 | 12186 | 21523 | 33234 | 50397 | 66376 | 114910 | 145824 |
| 2014 | 407 | 2582 | 5227 | 12006 | 21604 | 33366 | 50670 | 66667 | 116163 | 148589 |
| 2015 | 512 | 2914 | 5591 | 13168 | 22149 | 34053 | 51750 | 68155 | 120138 | 155734 |
| 2016 | 592 | 3371 | 6264 | 14658 | 22869 | 34829 | 52679 | 69282 | 123137 | 159416 |
| 2017 | 748 | 4072 | 7292 | 15629 | 23058 | 34886 | 52332 | 68602 | 122099 | 156700 |
| 2018 | 914 | 4790 | 8558 | 16488 | 23517 | 35177 | 52313 | 68614 | 122561 | 158891 |

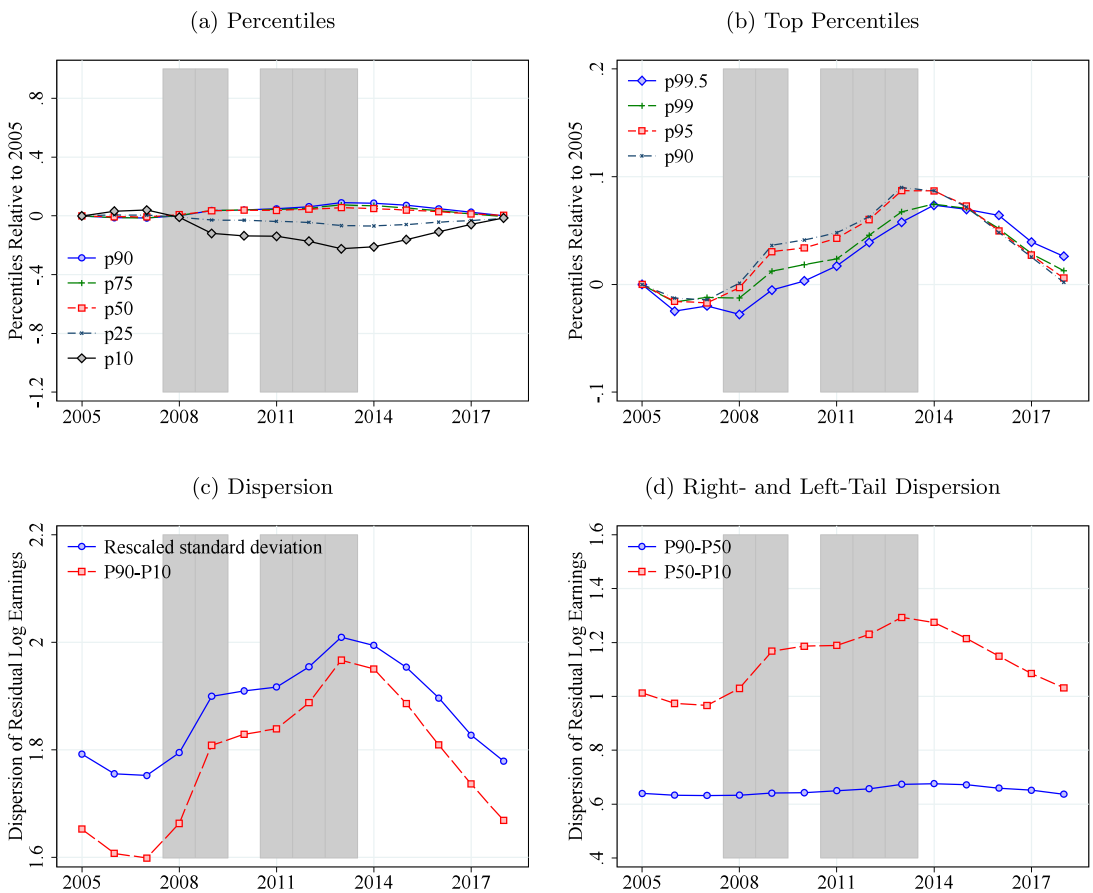
*Notes: B sample, positive income. Annual earnings are reported in 2018 U.S. dollars. Only males.*

Figure S-A1: Distribution of residual earnings in the population (males & females) after controlling for age




*Notes: CS sample, percentiles of residualized log annual earnings, after controlling for age. All percentiles are normalized to 0 in 2005. The shaded areas indicate recession years.*

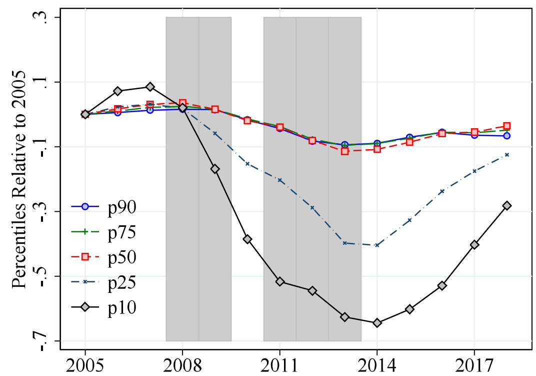
Figure S-A2: Distribution of residual earnings in the population (males & females) after controlling for age and education



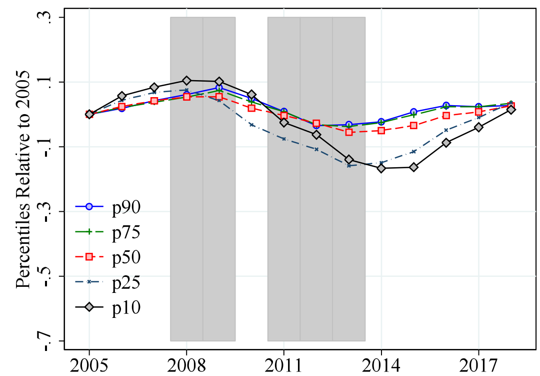

*Notes: CS sample, percentiles of residualized log annual earnings, after controlling for age and education. All percentiles are normalized to 0 in 2005. The shaded areas indicate recession years.*

Figure S-A3: Evolution of income percentiles and inequality, earnings & unemployment benefits

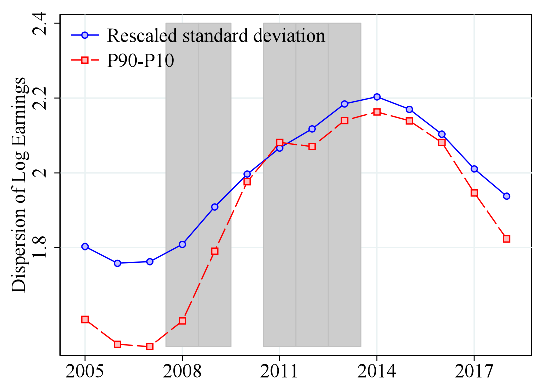
(a) Overall distribution: Males



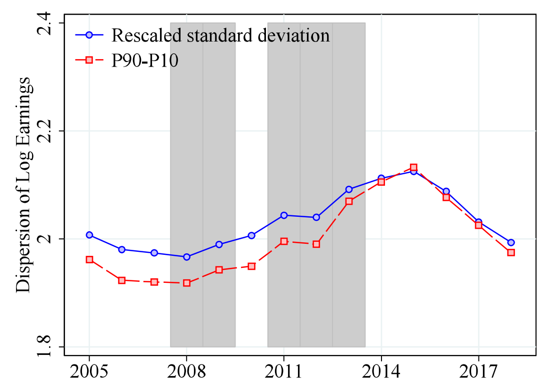

(b) Overall distribution: Females



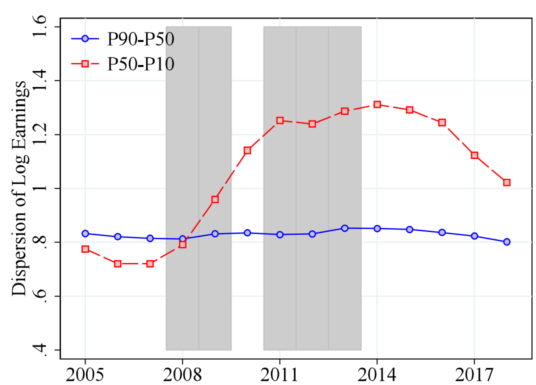

(c) Inequality: Males



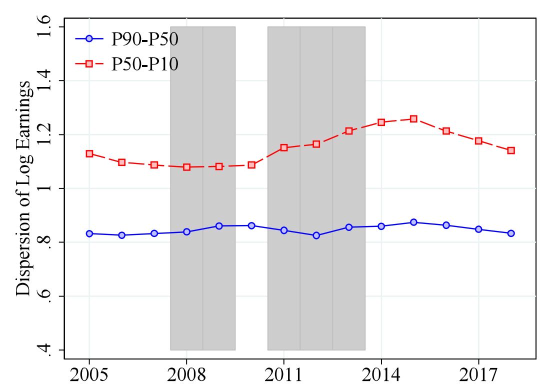

(d) Inequality: Females




(e) Upper & lower inequality: Males

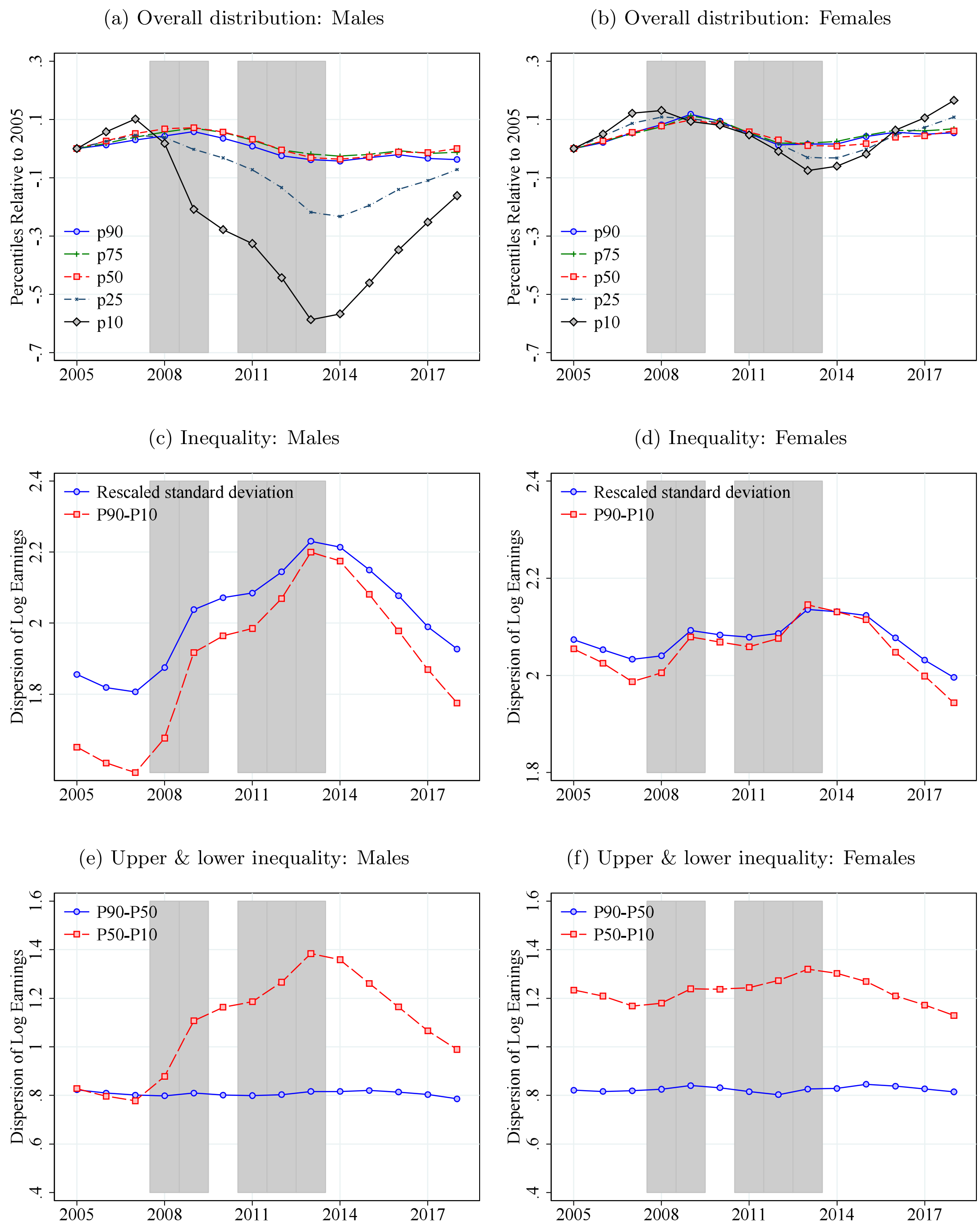



(f) Upper & lower inequality: Females



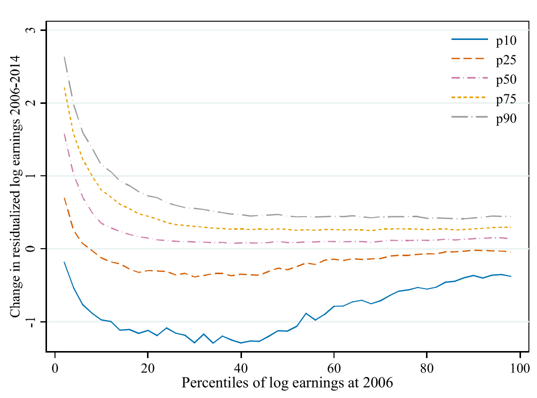

*Notes: CS sample, earnings and unemployment benefits. Top panel: percentiles of log annual income, by gender. All percentiles are normalized to 0 in 2005. Middle and bottom panels: P90-P10 difference and rescaled standard deviation, and P90-P50 and P50-P10 percentile differences. The shaded areas indicate recession years.*

Figure S-A4: Evolution of earnings percentiles and inequality, no immigrants




*Notes: CS sample, no immigrants. Top panel: percentiles of log annual earnings, by gender. All percentiles are normalized to 0 in 2005. Middle and bottom panels: P90-P10 difference and rescaled standard deviation, and P90-P50 and P50-P10 percentile differences. The shaded areas indicate recession years.*

Figure S-A5: Log earnings changes between 2006 and 2014 against initial earnings




*Notes: Non-missing observations on residualized log earnings in 2006 and 2014. On the x-axis we report percentiles of log earnings in 2006. On the y-axis we report the changes in residualized log earnings between 2006 and 2014.*

## S-B The welfare cost of income risk

Consider an individual with utility function $U_i(C_{it}) = \frac{(C_{it}-C_m)^{1-\theta_i}-1}{1-\theta_i}$, with consumption $C_{it} = \lambda(X_{it})Y_{it}$ for some proportionality factor $\lambda(X_{it})$. Suppose that

$$\ln(C_{it} - C_m) \,|\, X_{it} = x \sim \mathcal{N}(\mu(x), \sigma(x)^2).$$

The individual is willing to give up $a\%$ of consumption each period in order to eliminate income risk, where $a$ solves

$$U_i(\mathbb{E}(C_{it} \,|\, X_{it})(1-a)) = \mathbb{E}\left[U_i(C_{it}) \,|\, X_{it}\right].$$

Equivalently, omitting the dependence on $X_{it}$ for simplicity, $a$ solves

$$\begin{aligned}\left(\left(C_m + \exp\left(\mu + \frac{1}{2}\sigma^2\right)\right)(1-a) - C_m\right)^{1-\theta_i} &= \mathbb{E}\left[(C_{it} - C_m)^{1-\theta_i}\right] \\ &= \exp\left[(1-\theta_i)\mu + \frac{1}{2}(1-\theta_i)^2\sigma^2\right].\end{aligned}$$

It follows that

$$a = 1 - \frac{C_m + \exp\left[\mu + \frac{1}{2}(1-\theta_i)\sigma^2\right]}{C_m + \exp\left(\mu + \frac{1}{2}\sigma^2\right)}.$$

Hence, for small $\sigma$,

$$a = \frac{1}{2}\theta_i \frac{\exp(\mu)}{C_m + \exp(\mu)}\sigma^2 + o(\sigma^2).$$

Now, we have

$$\mathrm{CV} = \sqrt{\frac{2}{\pi}} \frac{\exp(\mu)}{\mathrm{C_m} + \exp(\mu)}\sigma + \mathrm{o}(\sigma).$$

Hence

$$a = \frac{\pi}{4}\theta_i \frac{C_m + \exp(\mu)}{\exp(\mu)}\mathrm{CV}^2 + \mathrm{o}(\sigma^2).$$

This implies (3), and (2) in the special case where $C_m = 0$.

## S-C Poisson regression results

Table S-C1: Poisson regression results

| | (1) Income levels | (2) Income absolute deviations |
|---|---|---|
| Log lagged income | 0.525 | 1.025 |
| | (0.107) | (0.257) |
| Log lagged income squared | 0.532 | -0.0107 |
| | (0.0864) | (0.203) |
| Log lagged income cubed | 0.0299 | -0.0251 |
| | (0.0291) | (0.0771) |
| Indicator that lagged income is zero | -4.798 | 2.732 |
| | (2.557) | (4.829) |
| Age | -0.0666 | -0.0251 |
| | (0.00875) | (0.0317) |
| Age squared | 0.000615 | -0.000444 |
| | (0.000102) | (0.00039) |
| Education: lower secondary | 0.102 | -0.0280 |
| | (0.0183) | (0.0905) |
| Education: upper secondary | 0.315 | 0.347 |
| | (0.0204) | (0.0955) |
| Education: college | 0.733 | 0.859 |
| | (0.0257) | (0.146) |
| Days worked in past year | -0.00134 | -0.00382 |
| | (0.000315) | (0.000978) |
| Indicator that out-of-work income is zero | -1.409 | -2.475 |
| | (0.181) | (0.631) |
| Log out-of-work income in past year | -0.997 | -1.393 |
| | (0.0917) | (0.321) |
| Indicator that worked full year in past year | -0.0214 | 0.0136 |
| | (0.0416) | (0.201) |
| Indicator that worked full year in past two years | 0.00279 | -0.414 |
| | (0.0343) | (0.221) |
| Indicator that worked full year in past three years | 0.0797 | 0.536 |
| | (0.0242) | (0.262) |
| Permanent contract in past year | -0.0149 | 0.173 |
| | (0.0236) | (0.138) |
| Full-time contract in past year | 0.219 | 0.225 |
| | (0.0359) | (0.159) |
| Intercept | 11.11 | 11.08 |
| | (0.185) | (0.657) |
| $N$ | 3111191 | 3111191 |

*Notes: B sample. Robust standard errors in parentheses, clustered at the individual level. In column (2), the dependent variable is $|Y_{it} - \exp(X_{it}'\widehat{\beta})|$, where $\widehat{\beta}$ is shown in column (1). The standard errors in column (2) are computed using a cluster bootstrap with 100 repetitions to account for the fact that $\widehat{\beta}$ is estimated. Macro predictors and interactions with age and age squared are included in the regressions, but omitted from the table for conciseness.*

## S-D Unobserved heterogeneity: a grouped fixed-effects approach

In this section we describe how we allow for unobserved predictors. To implement the grouped fixed-effects approach of Bonhomme et al. (2022), one possibility would be to group individuals based on their mean income. However, in an unbalanced panel this approach tends to mix individual-specific heterogeneity and age, particularly when there is a strong life-cycle component to income. To account for age, we proceed in two steps.

In the first step, we maximize the Poisson log likelihood

$$\sum_{i,t} \left[ Y_{it} \widetilde{X}_{it}' \beta(k_i) - \exp(\widetilde{X}_{it}' \beta(k_i)) \right], \tag{S-D6}$$

with respect to parameters $\beta(k)$ and group indicators $k_i$, where $\widetilde{X}_{it} = (1, age_{it}, age_{it}^2)'$. To implement the minimization, we use a Lloyd-like algorithm (see Bonhomme and Manresa, 2015). We start with 20 randomly chosen parameter values, and select the solution that corresponds to the highest value of the objective function. Given each starting value, we stop the algorithm when the change in the log likelihood is less than $10^{-10}$. This first step gives us parameters $\widetilde{\beta}(k)$ and group indicators $\widetilde{k}_i$.

In the second step, we include all our macro and micro predictors $X_{it}$. We aim to maximize

$$\sum_{i,t} \left[ Y_{it} X_{it}' \beta(k_i) - \exp(X_{it}' \beta(k_i)) \right], \tag{S-D7}$$

again with respect to parameters $\beta(k)$ and group indicators $k_i$. In this specification, we account for group effects in the intercept and the coefficients of age and age squared. We use 10 iterations of a Lloyd-like algorithm. The group indicators $\widetilde{k}_i$ provide a starting value to initiate the algorithm. This second step gives us parameters $\widehat{\beta}(k)$ and group indicators $\widehat{k}_i$, which are the ones we use to construct our prediction $\exp(X_{it}'\widehat{\beta}(\widehat{k}_i))$, which is the denominator of CV. We proceed similarly for the numerator. Hence, the CV coefficient is constructed using two sets of groups.

We apply the method to the B sample, restricted to individuals with at least 4 observations, using 4 groups for both the numerator and the denominator of CV. In Online Appendix Figure S-D1 we show the income profiles by age for the estimated clusters that we obtain

Table S-D1: Education Distribution of Individuals by Cluster

(a) Mean clusters

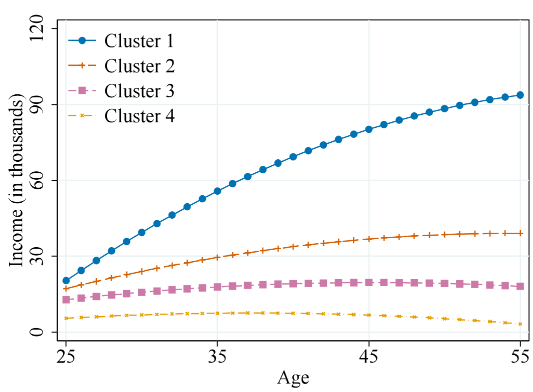
| | | Education (Proportion of Indivs.) | | | |
|---|---|---|---|---|---|
| Cluster | # of Indiv. | Primary | Lower Sec. | Upper Sec. | College |
| 1 | 20002 | 0.16 | 0.33 | 0.27 | 0.24 |
| 2 | 96641 | 0.17 | 0.39 | 0.25 | 0.19 |
| 3 | 132677 | 0.16 | 0.43 | 0.25 | 0.16 |
| 4 | 56827 | 0.23 | 0.40 | 0.23 | 0.14 |

(b) Absolute deviation clusters

| | | Education (Proportion of Indivs.) | | | |
|---|---|---|---|---|---|
| Cluster | # of Indiv. | Primary | Lower Sec. | Upper Sec. | College |
| 1 | 73778 | 0.17 | 0.43 | 0.24 | 0.17 |
| 2 | 100890 | 0.17 | 0.39 | 0.25 | 0.19 |
| 3 | 51268 | 0.20 | 0.42 | 0.23 | 0.15 |
| 4 | 80211 | 0.17 | 0.39 | 0.27 | 0.17 |

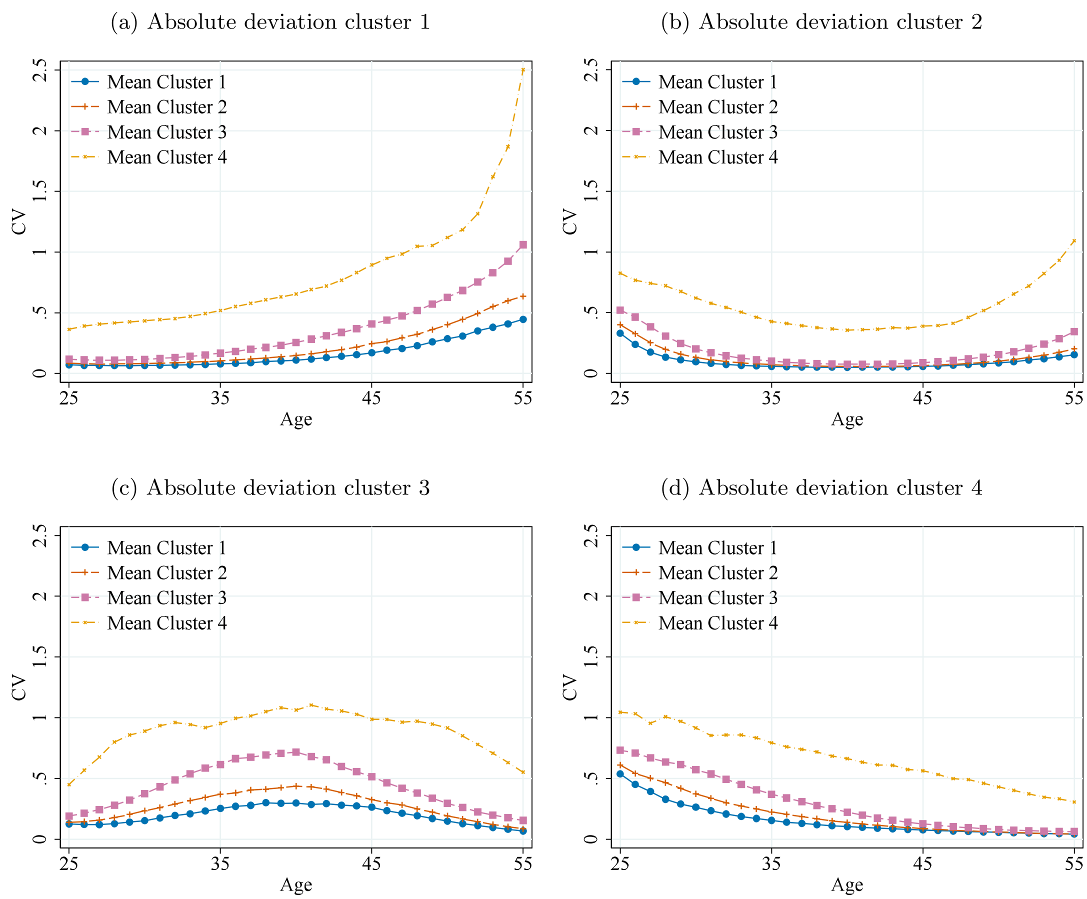
*Notes: B sample, individuals with at least 4 observations prior to 2018. Specification with unobserved heterogeneity, 4 groups. The mean clusters correspond to the prediction of income levels, the absolute deviation clusters correspond to the prediction of income absolute deviations.*

Figure S-D1: Predicted age income profiles for the estimated mean groups ($K = 4$)




*Notes: B sample, individuals with at least 4 observations prior to 2018. Specification with unobserved heterogeneity, 4 groups. The mean clusters correspond to the prediction of income levels, the absolute deviation clusters correspond to the prediction of income absolute deviations.*

Figure S-D2: Average CV over age, by mean cluster and absolute deviation cluster




*Notes: B sample, individuals with at least 4 observations prior to 2018. Specification with unobserved heterogeneity, 4 groups. The mean clusters correspond to the prediction of income levels, the absolute deviation clusters correspond to the prediction of income absolute deviations.*

using the above algorithm to predict income levels (the "mean clusters"). The clusters differ not only in the level of income, but also in the curvature of the profiles. In Online Appendix Figure S-D2 we show the CV profiles by age for all combinations of the mean clusters and the clusters that we obtain when predicting income absolute deviations (the "absolute deviation clusters"). We see that, while the former tends to capture differences in risk levels between individuals, the latter tends to pick up differences in age profiles. Lastly, in Online Appendix Table S-D1 we show the number of individuals in each cluster and the corresponding distribution of educational attainment. We find that the mean clusters are correlated with education, consistently with the fact that the higher educated tend to face lower risk levels. In contrast, the absolute deviation clusters are virtually independent of education.

## S-E Enforcing non-negativity of outcomes in quantile regression

Let $Y \mid X$ be a non-negative random variable with quantile function $g(x, \tau)$. In our application, $Y$ is income or income absolute deviation, and $X$ includes our micro and macro predictors. Let $\Pr(Y = 0|X = x) = \pi(x)$. Thus, $g(x, \tau) = 0$ for $\tau \leq \pi(x)$. Also,

$$\Pr(Y \leq g(x, \tau) \mid Y > 0, \tau > \pi(x), X = x) = \frac{\tau - \pi(x)}{1 - \pi(x)}.$$

Denote the $s$-conditional quantile of $Y$ given $Y > 0, X = x$ by $Q_s(Y \mid Y > 0, X = x) = \psi(x, s)$ so that

$$g(x, \tau) = \begin{cases} 0 & \text{for } \tau \leq \pi(x) \\ \psi\left(x, \frac{\tau - \pi(x)}{1 - \pi(x)}\right) & \text{for } \tau > \pi(x) \end{cases}.$$

For $\pi(x) \approx 0$, we have $g(x, \tau) \approx \psi(x, \tau)$.

An estimator of $g(x, \tau)$ that enforces non-negativity is as follows. First, we obtain the estimates $\widehat{\psi}(x, s) = \exp[\widehat{\gamma}(s)'\varphi(x)]$, and, using logit, $\widehat{\pi}(x) = \Lambda\left[\widehat{\beta}'\varphi(x)\right]$ where $\Lambda(v) = \exp(v)/(1 + \exp(v))$. To get $\widehat{\gamma}(s)$, we run linear quantile regressions of log income on $\varphi(x)$ in the subsample with positive income; $\widehat{\beta}$ is a logit estimate; and $\varphi(x)$ is a vector of functions of $x$. Finally, we compute:

$$\widehat{g}(x, \tau) = \begin{cases} 0 & \text{for } \tau \leq \widehat{\pi}(x) \\ \widehat{\psi}\left(x, \frac{\tau - \widehat{\pi}(x)}{1 - \widehat{\pi}(x)}\right) & \text{for } \tau > \widehat{\pi}(x) \end{cases}.$$

To ease the computational burden, we model $\gamma(s)$ as piecewise linear interpolating splines on a grid, $[\tau_1, \tau_2], [\tau_2, \tau_3], ..., [\tau_{L-1}, \tau_L]$, contained in the unit interval. The intercept coefficients on $(0, \tau_1]$ and $[\tau_L, 1)$ are parameterized as the quantiles of an exponential distribution on their respective supports. In practice, we use an equally spaced grid on the unit interval with $L = 11$.

## S-F Estimating measures of location and dispersion from subjective probabilistic income expectations

For each respondent in the Spanish Survey of Household Finances (EFF) who answers the subjective probabilistic income expectations question described in Section 6, we observe the fraction of points $\hat{p}_j$ allocated to each event $j = 1, \ldots, 5$ (adding up to 1). Here we present a simple approach to calculate summary measures of location and dispersion from these observations under the assumption that the underlying probabilities are normally distributed (with mean $\mu$ and standard deviation $\sigma$). That is, we assume that the underlying process for next year's log income is a random walk with a household-specific drift $\mu_i$ and normally distributed shocks with a household-specific standard deviation $\sigma_i$. The household index is omitted in the text for conciseness.

Under normality, $p_1 = \Phi(-0.1\beta - \alpha)$, $p_2 = \Phi(-0.02\beta - \alpha) - \Phi(-0.1\beta - \alpha)$, $p_3 = \Phi(0.02\beta - \alpha) - \Phi(-0.02\beta - \alpha)$, $p_4 = \Phi(0.1\beta - \alpha) - \Phi(0.02\beta - \alpha)$, $p_5 = 1 - \Phi(0.1\beta - \alpha)$, for $\alpha = \mu/\sigma$ and $\beta = 1/\sigma$. Elicited probabilities $\hat{p}_j$ can be regarded as noisy measurements of $p_j$ due to rounding and the inherent randomness in the elicitation process. If the $\hat{p}_j$ are regarded as sample frequencies from a hypothetical random sample of size $m$, they are the unrestricted maximum likelihood estimates of the $p_j$ from the multinomial log likelihood:

$$L(p) = \sum_j m\hat{p}_j \log p_j.$$

Alternatively, $p = (p_1, \ldots, p_4)$ can be estimated as the posterior mean of a posterior distribution proportional to $\exp[L(p) + \log \pi(p)]$, for some chosen prior $\pi(p)$ and value of $m$ (e.g., $m = 10$). A conventional option is to use Jeffreys prior, $\log \pi(p) = -\frac{1}{2}\sum_{j=1}^{5} \log p_j + C$, for some normalizing constant $C$. This is a Dirichlet distribution of order $J = 5$, which is the conjugate prior of the multinomial, therefore the posterior is also Dirichlet with posterior means given by:

$$\tilde{p}_j = \frac{\hat{p}_j + \frac{1}{2m}}{1 + \frac{J}{2m}}.$$

Jeffreys prior adds $J/2$ observations to the likelihood with equally distributed probabilities. The modified estimator $\tilde{p}_j$ has the advantage that it takes values in the open interval $(0,1)$ so that the inverse normal cdf transformation is still defined when $\hat{p}_j = 0$ or 1. In the present statistical framework, $m$ measures the accuracy of the process of eliciting subjective probabilities.

We implement this approach, using a Berkson estimator that enforces the Gaussian restrictions on the posterior means $\tilde{p}_j$. This estimator is based on the inverse normal probabilities:

$$\begin{aligned}
q_1 &= \Phi^{-1}(1-c_1) = 0.1\beta + \alpha \\
q_2 &= \Phi^{-1}(1-c_2) = 0.02\beta + \alpha \\
q_3 &= \Phi^{-1}(1-c_3) = -0.02\beta + \alpha \\
q_4 &= \Phi^{-1}(1-c_4) = -0.1\beta + \alpha
\end{aligned}$$

where the $c_j$ are the cumulative probabilities $c_j = \sum_{k=1}^{j} p_k$. Sample counterparts are

$$\tilde{c}_j = \sum\nolimits_{k=1}^{j} \tilde{p}_k = \frac{\hat{c}_j + \frac{j}{2m}}{1 + \frac{J}{2m}}$$

and $\tilde{q}_j = \Phi^{-1}(1-\tilde{c}_j)$. To estimate $\mu$ and $\sigma$ we choose a particular solution of the previous system with an intuitive interpretation:

$$\begin{aligned}
\tilde{\mu} &= \frac{1}{2} \times \frac{(\tilde{q}_1 + \tilde{q}_4) + (\tilde{q}_2 + \tilde{q}_3)}{5(\tilde{q}_1 - \tilde{q}_4) + 25(\tilde{q}_2 - \tilde{q}_3)}, \\
\tilde{\sigma} &= \frac{2}{5(\tilde{q}_1 - \tilde{q}_4) + 25(\tilde{q}_2 - \tilde{q}_3)}.
\end{aligned}$$

Lastly, mimicking the fact that the maximum likelihood estimator of $\theta = (\alpha, \beta)$ is $\widehat{\theta} = \arg\max_\theta \sum_j \widehat{p}_j \ln p_j(\theta)$, an alternative method to enforce the restrictions on the posterior means $\widetilde{p}_j$ would be to compute

$$\widetilde{\theta} = \arg\max_\theta \sum_j \widetilde{p}_j \ln p_j(\theta).$$

Nevertheless, in our empirical calculations of subjective risks we relied on the Berkson estimator, which has a simple closed-form expression.

## S-G Additional tables and figures on robustness checks

### S-G.1 After-tax income

Table S-G1: Effective Tax Rates

| year | base_1 | tau_1 | base_2 | tau_2 | base_3 | tau_3 | base_4 | tau_4 | base_5 | tau_5 | base_6 | tau_6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2005 | 0 | 8.72 | 4080.0 | 4.42 | 14076.0 | 10.28 | 26316.0 | 16.74 | 45900.0 | 26.43 | . | . |
| 2006 | 0 | 11.29 | 4161.6 | 4.71 | 14357.5 | 10.52 | 26842.3 | 17.03 | 46818.0 | 26.89 | . | . |
| 2007 | 0 | 5.68 | 17360.0 | 12.32 | 32360.0 | 18.49 | 52360.0 | 27.5 | . | . | . | . |
| 2008 | 0 | 3.68 | 17707.2 | 10.51 | 33007.2 | 17.38 | 53407.2 | 26.83 | . | . | . | . |
| 2009 | 0 | 3.31 | 17707.2 | 10.45 | 33007.2 | 17.28 | 53407.2 | 26.66 | . | . | . | . |
| 2010 | 0 | 4.17 | 17707.2 | 12.25 | 33007.2 | 18.34 | 53407.2 | 27.03 | . | . | . | . |
| 2011 | 0 | 3.74 | 17707.2 | 12.21 | 33007.2 | 18.25 | 53407.2 | 26.42 | 120000.2 | 34.59 | 175000.2 | 39.58 |
| 2012 | 0 | 3.75 | 17707.2 | 12.93 | 33007.2 | 19.47 | 53407.2 | 28.28 | 120000.2 | 37.61 | 175000.2 | 43.31 |
| 2013 | 0 | 3.62 | 17707.2 | 13.12 | 33007.2 | 19.55 | 53407.2 | 28.32 | 120000.2 | 37.75 | 175000.2 | 43.80 |
| 2014 | 0 | 3.48 | 17707.2 | 13.12 | 33007.2 | 19.52 | 53407.2 | 28.16 | 120000.2 | 37.52 | 175000.2 | 43.68 |
| 2015 | 0 | 1.68 | 12450.0 | 5.95 | 20200.0 | 12.66 | 34000.0 | 18.81 | 60000.0 | 28.68 | . | . |
| 2016 | 0 | 2.04 | 12450.0 | 6.02 | 20200.0 | 12.89 | 35200.0 | 19.22 | 60000.0 | 28.62 | . | . |
| 2017 | 0 | 2.47 | 12450.0 | 6.20 | 20200.0 | 12.79 | 35200.0 | 19.38 | 60000.0 | 28.92 | . | . |
| 2018 | 0 | 2.47 | 12450.0 | 6.20 | 20200.0 | 12.79 | 35200.0 | 19.38 | 60000.0 | 28.92 | . | . |

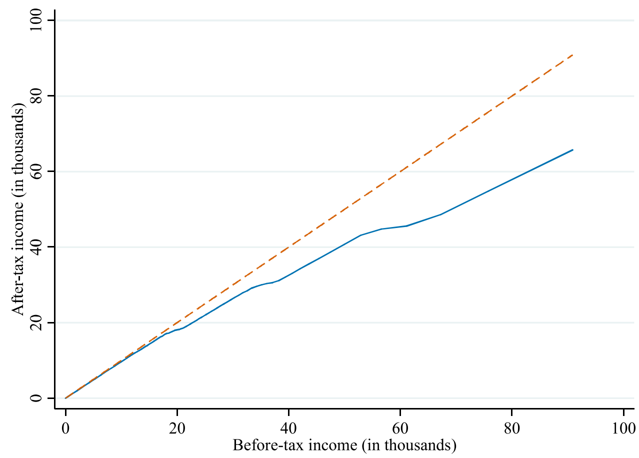
*Notes: "base_x" represents the upper and lower bounds of income brackets. "tau_x" represents the average effective tax rates. All income bracket bounds are in nominal euros. Average effective tax rates are in percent.*

Table S-G2: Income risk over the period, in numbers, after-tax income

| | All | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P90/P10 | 9.17 | 5.18 | 5.65 | 5.72 | 6.76 | 9.16 | 9.89 | 10.95 | 12.68 | 13.32 | 11.91 | 10.37 | 9.31 | 8.25 |
| P90/P50 | 6.41 | 3.97 | 4.20 | 4.19 | 4.92 | 6.41 | 6.70 | 7.23 | 8.17 | 8.46 | 7.75 | 6.93 | 6.52 | 5.81 |
| P50/P10 | 1.43 | 1.30 | 1.34 | 1.36 | 1.37 | 1.43 | 1.48 | 1.51 | 1.55 | 1.58 | 1.54 | 1.50 | 1.43 | 1.42 |
| p10 | 0.07 | 0.08 | 0.08 | 0.08 | 0.08 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.08 | 0.07 |
| p25 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 |
| p50 | 0.11 | 0.10 | 0.10 | 0.10 | 0.11 | 0.10 | 0.10 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.10 |
| p75 | 0.32 | 0.23 | 0.24 | 0.24 | 0.27 | 0.34 | 0.36 | 0.40 | 0.45 | 0.46 | 0.42 | 0.35 | 0.33 | 0.29 |
| p90 | 0.67 | 0.40 | 0.43 | 0.43 | 0.52 | 0.67 | 0.70 | 0.80 | 0.90 | 0.93 | 0.85 | 0.75 | 0.70 | 0.61 |

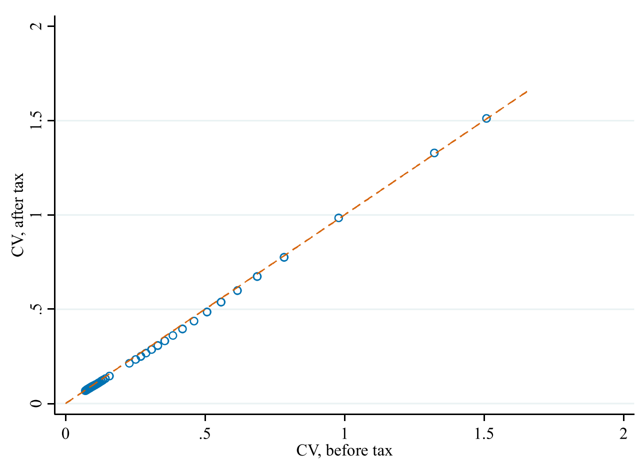
*Notes: B sample. Exponential specification, using all macro and micro predictors. After-tax income.*

Figure S-G1: Before-tax and after-tax income




*Notes: Income in thousands of euros. See the text for how we construct after-tax income.*

Figure S-G2: Quantile-quantile plot of before-tax and after-tax CV




*Notes: B sample. On the x-axis we report the percentiles of CV based on before-tax income. On the y-axis we report the percentiles of CV based on after-tax income.*

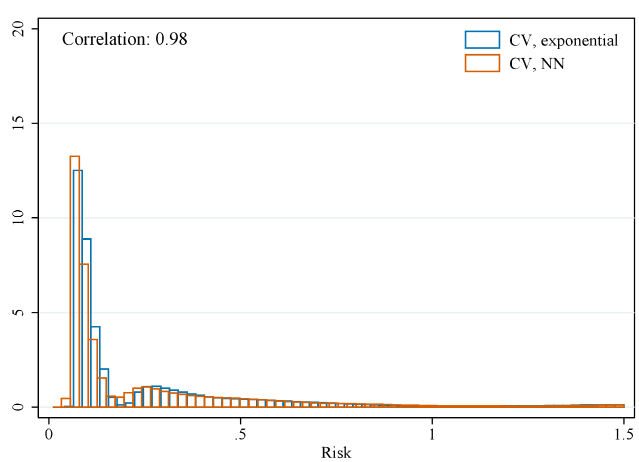
## S-G.2 Neural network specification

Table S-G3: Income risk over the period, in numbers, neural network specification

| | All | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P90/P10 | 10.82 | 6.41 | 6.96 | 7.04 | 7.85 | 9.33 | 10.52 | 12.51 | 14.16 | 14.93 | 13.98 | 12.59 | 11.43 | 10.63 |
| P90/P50 | 6.63 | 4.31 | 4.64 | 4.69 | 5.27 | 6.03 | 6.55 | 7.55 | 8.09 | 8.07 | 7.66 | 7.10 | 6.76 | 6.49 |
| P50/P10 | 1.63 | 1.49 | 1.50 | 1.50 | 1.49 | 1.55 | 1.61 | 1.66 | 1.75 | 1.85 | 1.83 | 1.77 | 1.69 | 1.64 |
| p10 | 0.07 | 0.07 | 0.06 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 | 0.06 | 0.06 | 0.06 | 0.07 | 0.06 |
| p25 | 0.08 | 0.08 | 0.07 | 0.08 | 0.08 | 0.08 | 0.08 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.08 | 0.07 |
| p50 | 0.11 | 0.10 | 0.10 | 0.10 | 0.11 | 0.11 | 0.11 | 0.11 | 0.11 | 0.12 | 0.11 | 0.11 | 0.12 | 0.10 |
| p75 | 0.34 | 0.23 | 0.22 | 0.24 | 0.30 | 0.38 | 0.40 | 0.42 | 0.45 | 0.49 | 0.46 | 0.37 | 0.37 | 0.28 |
| p90 | 0.71 | 0.45 | 0.45 | 0.47 | 0.58 | 0.66 | 0.71 | 0.81 | 0.87 | 0.94 | 0.87 | 0.78 | 0.81 | 0.64 |

*Notes: B sample. Neural network specification with Poisson loss. One layer with 8 nodes for the conditional mean and 7 nodes for the conditional mean absolute deviation.*

Figure S-G3: Two specifications of CV, exponential and neural network




*Notes: B sample, using all macro and micro predictors. The correlation coefficient is computed after trimming the 99th percentiles of both CV measures.*

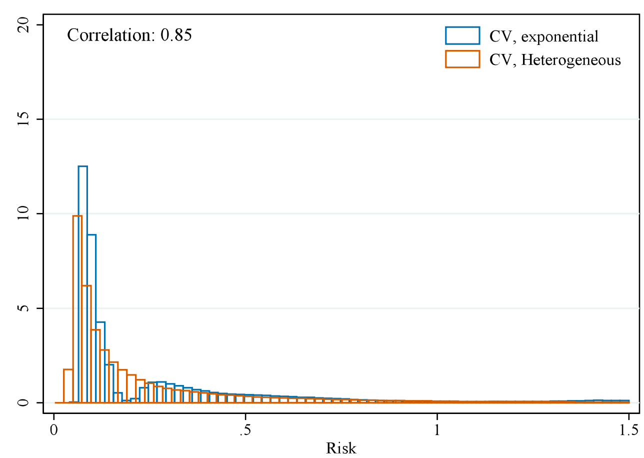
### S-G.3 Specification with unobserved heterogeneity

Table S-G4: Income risk over the period, in numbers, specification with unobserved heterogeneity

| | All | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P90/P10 | 10.59 | 6.48 | 6.86 | 7.41 | 8.73 | 10.72 | 11.25 | 12.09 | 13.29 | 13.72 | 12.97 | 11.76 | 10.86 | 9.60 |
| P90/P50 | 5.00 | 3.35 | 3.56 | 3.83 | 4.35 | 4.98 | 5.03 | 5.28 | 5.56 | 5.69 | 5.70 | 5.46 | 5.27 | 4.74 |
| P50/P10 | 2.12 | 1.93 | 1.93 | 1.94 | 2.01 | 2.15 | 2.24 | 2.29 | 2.39 | 2.41 | 2.28 | 2.15 | 2.06 | 2.03 |
| p10 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 | 0.05 | 0.05 | 0.05 |
| p25 | 0.07 | 0.08 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
| p50 | 0.12 | 0.12 | 0.11 | 0.11 | 0.11 | 0.12 | 0.12 | 0.13 | 0.14 | 0.14 | 0.13 | 0.12 | 0.11 | 0.11 |
| p75 | 0.27 | 0.21 | 0.21 | 0.21 | 0.24 | 0.28 | 0.31 | 0.34 | 0.37 | 0.37 | 0.33 | 0.28 | 0.25 | 0.23 |
| p90 | 0.60 | 0.39 | 0.40 | 0.42 | 0.50 | 0.59 | 0.63 | 0.71 | 0.77 | 0.78 | 0.73 | 0.64 | 0.60 | 0.53 |

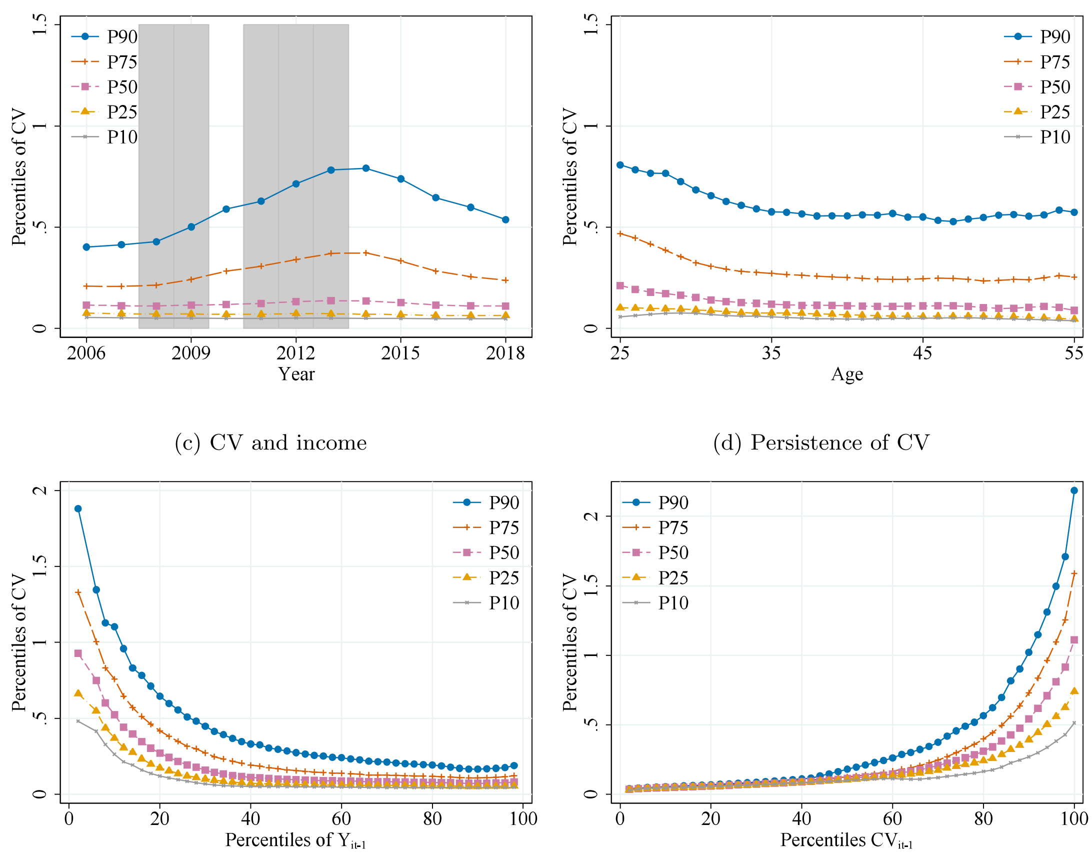
*Notes: B sample, individuals with at least 4 observations prior to 2018. Exponential specification, using all macro and micro predictors and unobserved heterogeneity. 4 groups.*

Figure S-G4: Two specifications of CV, with and without unobserved heterogeneity




*Notes: B sample, individuals with at least 4 observations prior to 2018. Exponential specification, using all macro and micro predictors, and unobserved heterogeneity in the right graph (4 groups). The correlation coefficient is computed after trimming the 99th percentiles of both CV measures.*

Figure S-G5: CV, specification with unobserved heterogeneity, 6 groups




(a) Over the period, percentiles

(b) Over the period, percentiles

(c) CV and income

(d) Persistence of CV

*Notes: B sample, individuals with at least 4 observations prior to 2018. Exponential specification, using all macro and micro predictors, and unobserved heterogeneity. 6 groups.*

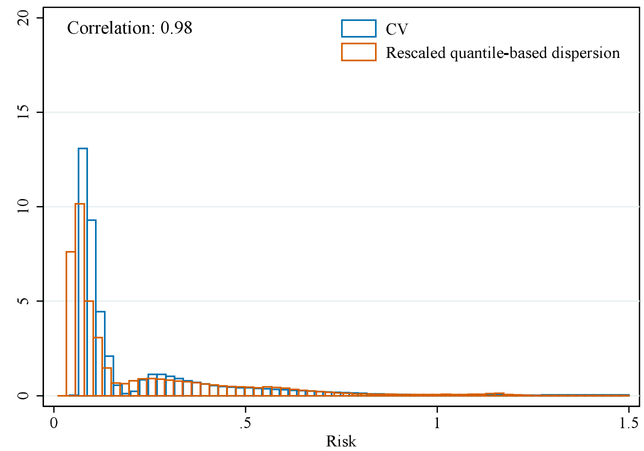
Table S-G5: Income risk over the period, in numbers, specification with unobserved heterogeneity, 6 groups

| | All | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P90/P10 | 11.99 | 7.33 | 7.81 | 8.34 | 9.76 | 11.90 | 12.62 | 13.77 | 15.23 | 15.75 | 14.94 | 13.65 | 12.64 | 11.28 |
| P90/P50 | 5.04 | 3.47 | 3.68 | 3.87 | 4.34 | 4.99 | 5.09 | 5.36 | 5.70 | 5.83 | 5.80 | 5.57 | 5.36 | 4.87 |
| P50/P10 | 2.38 | 2.11 | 2.12 | 2.16 | 2.25 | 2.39 | 2.48 | 2.57 | 2.67 | 2.70 | 2.58 | 2.45 | 2.36 | 2.32 |
| p10 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| p25 | 0.07 | 0.08 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 | 0.06 | 0.06 |
| p50 | 0.12 | 0.12 | 0.11 | 0.11 | 0.12 | 0.12 | 0.12 | 0.13 | 0.14 | 0.14 | 0.13 | 0.12 | 0.11 | 0.11 |
| p75 | 0.27 | 0.21 | 0.21 | 0.21 | 0.24 | 0.28 | 0.31 | 0.34 | 0.37 | 0.37 | 0.33 | 0.28 | 0.26 | 0.24 |
| p90 | 0.60 | 0.40 | 0.41 | 0.43 | 0.50 | 0.59 | 0.63 | 0.71 | 0.78 | 0.79 | 0.74 | 0.65 | 0.60 | 0.54 |

*Notes: B sample, individuals with at least 4 observations prior to 2018. Exponential specification, using all macro and micro predictors and unobserved heterogeneity. 6 groups.*

## S-G.4 Beyond the CV

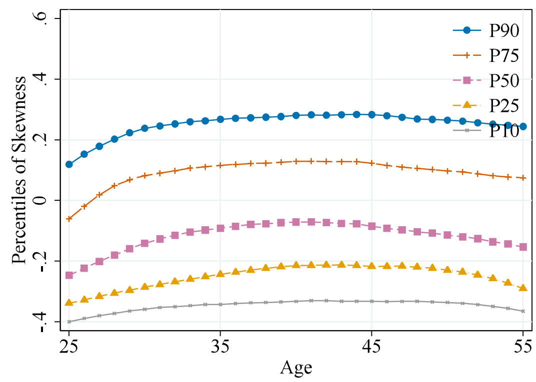
Figure S-G6: Comparing CV and quantile-based dispersion



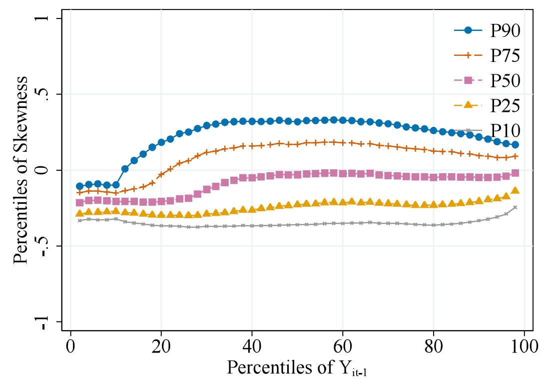

*Notes: B sample, with positive income. CV is our CV measure (i.e., conditional mean absolute deviation divided by conditional mean). Quantile-based dispersion is* $P90(X_{it}) - P10(X_{it})$ *(rescaled), where* $P90(X_{it})$ *and* $P10(X_{it})$ *are estimated using linear quantile regressions of log income on all macro and micro predictors. The correlation coefficient is computed after trimming the 99th percentiles of both CV measures.*

Figure S-G7: Quantile-based skewness, additional results

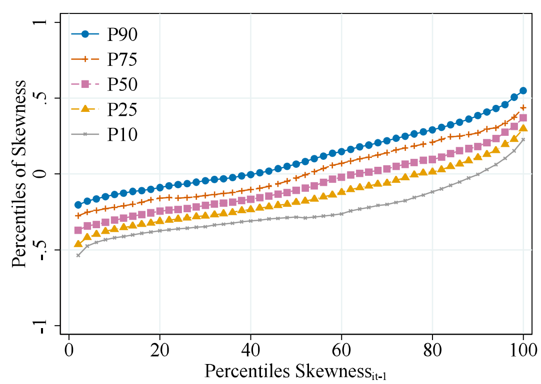
(a) Over the life cycle, percentiles




(b) Skewness and income




(c) Persistence of quantile-based skewness




*Notes: B sample, with positive income. Quantile-based measure of skewness risk,* $\frac{P90(X_{it})-2P50(X_{it})+P10(X_{it})}{P90(X_{it})-P10(X_{it})}$*, where* $P90(X_{it})$*,* $P50(X_{it})$*, and* $P10(X_{it})$ *are estimated using linear quantile regressions of log income on all macro and micro predictors.*

## References

Bonhomme, Stéphane, Thibaut Lamadon, and Elena Manresa (2022) "Discretizing Unobserved Heterogeneity," *Econometrica*, 90 (2), 625–643, 10.3982/ECTA15238.

Bonhomme, Stéphane and Elena Manresa (2015) "Grouped Patterns of Heterogeneity in Panel Data," *Econometrica*, 83 (3), 1147–1184, https://doi.org/10.3982/ECTA11319.