# Capital and Labor Income Pareto Exponents across Time and Space

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**Abstract**

We estimate capital and labor income Pareto exponents across 348 country-year observations that span 51 countries over half a century. We document two stylized facts: (i) capital income is more unequally distributed than labor income; namely, the capital exponent (1–3) is smaller than labor (2–5), and (ii) capital and labor exponents are nearly uncorrelated. To explain these findings, we build an incomplete market model with job ladders and capital income risk that gives rise to a capital income Pareto exponent smaller than but nearly unrelated to the labor exponent. Our results suggest the importance of distinguishing income and wealth inequality.

**Keywords:** income fluctuation problem, inequality, power law.

**JEL codes:** C46, D15, D31, D52.

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# 1 Introduction

The purpose of this paper is to estimate and document the Pareto exponents for capital and labor income separately for as many countries and years as possible. We say that a positive random variable $X$ obeys a power law with Pareto exponent $\alpha > 0$ if the tail probability decays like a power function: $\mathrm{P}(X > x) \sim x^{-\alpha}$ for large $x$. In the context of the income distribution, the Pareto exponent characterizes the tail heaviness of high incomes and hence top tail inequality. Our study is motivated by the following two observations. First, we are not aware of a comprehensive study that documents the capital and labor income Pareto exponents separately for many countries and years, despite their importance. Second, the Pareto exponent has desirable properties relative to other popular inequality measures such as top income shares.

Consider the first point. Conceptually, capital and labor income are very different. While the former is the return for providing capital (wealth), the latter is the return for providing labor services, and there is no particular reason to expect a relation between the two. Although these two forms of income are conceptually distinct, it is often put together as just "income" and discussed in the context of inequality and related policies. If capital and labor income are quantitatively different, a policy design based on total income may be misleading. To give one example, consider the theory of optimal taxation (Saez, 2001), where the income Pareto exponent plays an important role. Saez and Stantcheva (2018) carefully distinguish capital and labor income and apply the theory of optimal taxation in the United States.

They find that with an income elasticity of $e = 0.5$, the optimal top marginal tax rate is about 50% for labor and 60% for capital (see their Figure 5). This difference directly comes from the fact that capital and labor income Pareto exponents are distinct. Thus, distinguishing capital and labor income inequality is potentially important for policy designs.

Consider the second point. In the applied literature such as Piketty (2003) and Piketty and Saez (2003), top income shares (such as the top 1% income share) are more commonly reported than the income Pareto exponent, perhaps because top shares are summary statistics that can be computed without specifying functional forms or can be understood by non-experts without special knowledge of statistics. However, Atkinson (2005) documents methodological problems regarding the cross-country comparison of top income shares, citing the differences in tax units (e.g., individual or household) and legislation (e.g., whether social security benefits are taxable). One of the reasons such issues arise is because it is not always clear how to define the population and measure small units. For example, suppose one is interested in the top 1% share of population in cities or fresh water surface area in lakes. Clearly the resulting numbers highly depend on how we define cities and lakes (versus villages and ponds). Using the Pareto exponents significantly alleviates these definition and measurement issues because the Pareto distribution is scale invariant (see Jessen and Mikosch, 2006 for a summary).

In this paper, we use the harmonized *Luxembourg Income Study* database (hereafter LIS) to document the capital and labor income Pareto exponents across all available 348 country-year observations that span 51 countries over half a century. We document two empirical findings. First, we find that the capital income Pareto exponent is roughly in the range 1–3 and is smaller than the labor income Pareto exponent, which ranges between 2–5. This implies that capital income is more unequally distributed than labor income. This fact is unsurprising and well known for a specific country or year (see, for example, the Lorenz curve in Figure 1 of Saez and Stantcheva, 2018). However, we are not aware of a comprehensive study that systematically analyzes datasets from many countries and years, and therefore our finding suggests that capital income is generally more unequal than labor income. More specifically, we formally test the equality of capital and labor income Pareto exponents and the null is rejected in 85% of samples. In every single case of rejection, the capital exponent is smaller than the labor exponent. Second, we find that the capital income Pareto exponent is nearly unrelated to the labor exponent. In particular, the correlation between the two exponents across countries is close to zero.

To explain our empirical findings, we build a simple incomplete market model with job ladders and capital income risk. In the model, agents get randomly promoted to the next job ladder. Because individual income follows a random growth process, we obtain a Pareto-tailed labor income distribution. The agents also save assets and face idiosyncratic investment risk, which generates a Pareto-tailed wealth (hence capital income) distribution. Because the capital income Pareto exponent is mainly determined by the asset return distribution, while the labor income Pareto exponent is mainly determined by the income growth distribution, the relation between the two is weak. Furthermore, we analytically characterize the capital and labor income Pareto exponents and show that the former tends to be smaller than the latter for common parametrization. Our results suggest the importance of distinguishing income and wealth inequality.

**Related literature** The power law behavior of income was first recognized by Pareto (1895, 1896, 1897), who used tabulation data of tax returns in many European countries. More recent research that employs micro data include Reed (2001) for U.S., Reed (2003) for U.S., Canada, Sri Lanka, and Bohemia, Nirei and Souma (2007) for Japan, Toda (2011, 2012) for U.S., and Ibragimov and Ibragimov (2018) for Russia. Bandourian et al. (2002) estimate eleven parametric distributions (some of which exhibit Pareto tails) using 82 household labor income datasets from *Luxembourg Income Study* (LIS) as we do, though they neither focus on the Pareto exponent nor consider capital income. Atkinson and Piketty (2010, Table 13A.23) document income Pareto exponents across many countries and years estimated from top income share data based on tax returns. However, their estimates are based on total income, and since (as we document in Section 2.3) the capital income Pareto exponents tend to be smaller than labor exponents, their estimates are best understood as capital income (hence wealth) Pareto exponents. See Gabaix (2009) for an introduction to power law. We apply the recent result of Hoga (2018) to test the equality of capital and labor income Pareto exponents.

## 2 Pareto exponents across countries and years

In this section we estimate the capital and labor income Pareto exponents for all countries and years that are available in the LIS database, which spans

51 countries over half a century (348 country-year observations in total). See Appendix A for the data description.

## 2.1 Estimation method

For each country and year, we suppose that the (capital or labor) income observations $\{X_n\}_{n=1}^N$ are independent and identically distributed (i.i.d.) with cumulative distribution function (CDF) $F(x) = \mathrm{P}(X_n \le x)$. The assumption that the upper tail of income obeys a power law with Pareto exponent $\alpha > 0$ translates into the regular variation condition

$$1 - F(x) = x^{-\alpha}\ell(x) \tag{2.1}$$

for some slowly varying function $\ell$.[1] We are interested in estimating the Pareto exponent $\alpha$ for each country and year. For this purpose, we employ the Hill (1975) (maximum likelihood) estimator

$$\frac{1}{\widehat{\alpha}(k)} := \frac{1}{k}\sum_{n=1}^{k} \log\left(\frac{X_{n:N}}{X_{k:N}}\right). \tag{2.2}$$

Here $X_{n:N}$ denotes the $n$-th largest order statistic from the sample $\{X_n\}_{n=1}^N$ and $k \in \{1, \dots, N\}$ denotes the number of tail observations used to estimate the Pareto exponent.[2]

When the population distribution is known to be exactly Pareto (so $\ell$ in

[1] A function $\ell : (0, \infty) \to \mathbb{R}$ is said to be *slowly varying (at infinity)* if it is nonzero for sufficiently large $x$ and $\lim_{x\to\infty} \ell(tx)/\ell(x) = 1$ for each $t > 0$. See Bingham et al. (1987) for a comprehensive treatment of the theory of regular variation.

[2] We use the Hill estimator because it is most natural and popular. Gomes and Guillou (2015) review 13 commonly used estimators. Fedotenkov (2018) review more than 100.

(2.1) is zero below the minimum size $x_{\min}$ and constant above this threshold), it is well known that the Hill estimator for the full sample ($k = N$) is consistent, asymptotically normal, and asymptotically efficient because it is a maximum likelihood estimator. In practice, the CDF is not exactly Pareto and the researcher needs to select an appropriate value of $k$. For instance, if $F(x)$ satisfies

$$1 - F(x) = Cx^{-\alpha}(1 + Dx^{-\beta} + o(x^{-\beta}))$$

with some $\beta > 0$, then Hall (1982) shows that choosing $k = o(N^{2\beta/(2\beta+\alpha)})$ together with $k \to \infty$ as $N \to \infty$ is sufficient for consistency and asymptotic normality (see also Embrechts et al., 2013). Notice that this choice puts a bound on the growth rate of $k$.

Despite these asymptotic results, it is notoriously difficult to pick $k$ optimally in finite samples (Hall, 1990; Resnick and Stărică, 1997; Danielsson et al., 2001). In practice, researchers often plot the Hill estimator (2.2) over a range of $k$ to find a flat region or plot the log rank $\log 1, \dots, \log N$ against the log size $\log X_{1:N}, \dots, \log X_{N:N}$ to find a region that exhibits a straight line pattern and choose a size threshold to run the log-rank regression.[3][4] Unfortunately, this graphical approach is not feasible in our setting because LIS does

[3] Gabaix and Ibragimov (2011) study the asymptotic behavior of log rank regression and show that the standard error is larger by a factor of $\sqrt{2}$ than the Hill estimator. However, they do not discuss how to select the threshold. In their empirical application, they consider the size distribution of population in U.S. metropolitan statistical areas, which are already far into the tail and hence the threshold selection is less of an issue. Ibragimov and Ibragimov (2018) apply the same methodology to Russian household income data and consider the top 5% and 10% thresholds.

[4] An alternative approach is to estimate a parametric distribution $F$ that admits a Pareto upper tail by maximum likelihood using the entire sample. The double Pareto-lognormal distribution proposed by Reed (2003) and Reed and Jorgensen (2004) often performs best. See Toda (2012) for a horse race across several parametric distributions in the context of U.S. labor income.

not allow researchers to download the micro data for confidentiality concerns (researchers are required to submit their execution files to conduct statistical analyses) and there is little scope for exploratory graphical data analysis. To overcome this issue, we apply the recent work by Danielsson et al. (2016), who propose a quantile-based heuristic to choose $k$ in finite samples, which seems to work well as illustrated by their extensive simulation studies. Their approach can be explained as follows. The theoretical top $j/N$-quantile can be estimated by $X_{j:N}$. On the other hand, assuming a Pareto distribution in the upper tail, we can also estimate the quantile by $(k/j)^{1/\widehat{\alpha}(k)}X_{k:N}$, where $k$ is the number of tail observations used to estimate the Pareto exponent. Hence, we would want the Kolmogorov-Smirnov distance (in the quantile domain)

$$\max_{j=1,\dots,k}\left|X_{j:N}-(k/j)^{1/\widehat{\alpha}(k)}X_{k:N}\right| \tag{2.3}$$

to be small. Danielsson et al. (2016) propose to choose $k$ according to the min-max criterion

$$k^*=\operatorname*{arg\,min}_{k=k_{\min},\dots,k_{\max}}\max_{j=1,\dots,k}\left|X_{j:N}-(k/j)^{1/\widehat{\alpha}(k)}X_{k:N}\right|, \tag{2.4}$$

where $k_{\min}$ and $k_{\max}$ are thresholds set by the researcher to bound the minimum and maximum value of acceptable $k$. Below, we adopt this methodology to select the optimal $k$, where we set the bounds $k_{\min}=\lfloor 0.01N\rfloor$ and $k_{\max}=\lfloor 0.1N\rfloor$ so that we force the estimation sample to include at least the top 1% but no more than the top 10% observations. As a robustness check, we also consider setting $k^*=\lfloor 0.05N\rfloor$ (top 5% observations).

## 2.2 Capital and labor income Pareto exponents

We apply the automated estimation procedure described in Section 2.1 to estimate the capital and labor income Pareto exponents for all countries and years available in the LIS database. The database spans 51 countries across the years 1967–2016, with a total of 348 country-year observations. The point estimates of the capital and labor income Pareto exponents for each country and year as well as their standard errors can be found in Table 2 in Appendix C. For visibility, Figure 1 shows histograms and scatter plots of the capital and labor income Pareto exponents. The left and right panels show the results for the automatic procedure for threshold selection and the top 5% threshold, respectively.

The top panels of Figure 1 show the histograms of the capital and labor income Pareto exponents pooled across all available countries and years. The capital and labor income Pareto exponents are generally in the range 1–3 and 2–5, respectively. This suggests that (i) capital income is generally more unequally distributed than labor income, but (ii) there is significant heterogeneity in both capital and labor income inequality across countries and years. The bottom panels of Figure 1 show the scatter plots of the Pareto exponents together with the 45° degree line. We find that the correlation between the two exponents is weak. Furthermore, for the vast majority of countries and years, the capital income Pareto exponent is smaller than the labor exponent, again suggesting that capital income is more unequal than labor income.

How do the Pareto exponents evolve over time? Because countries appear

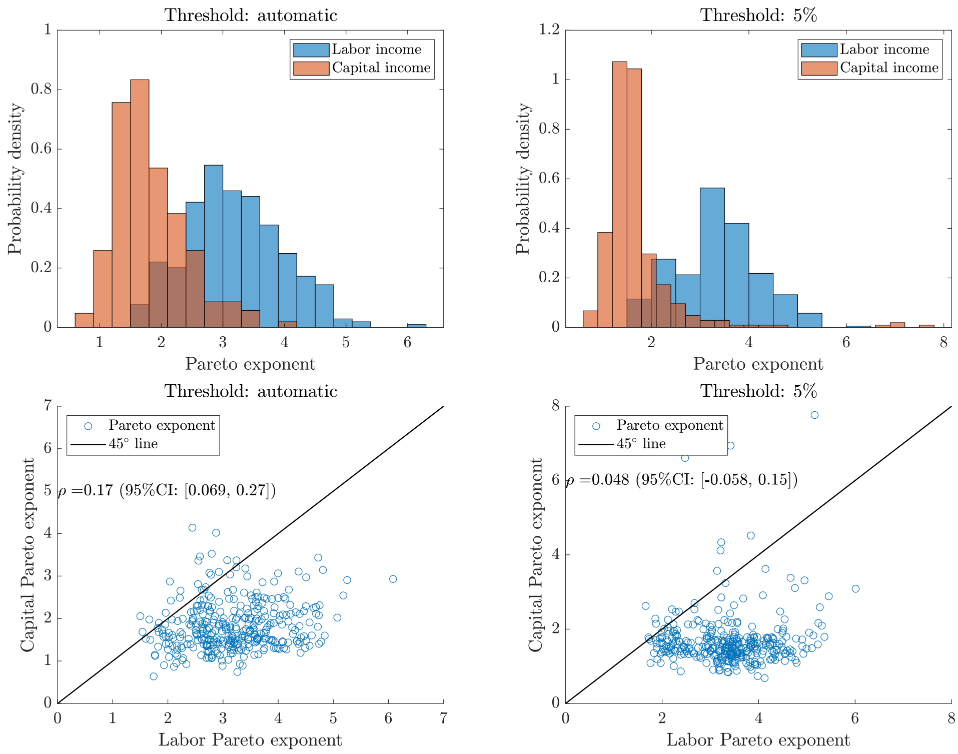



Figure 1: Histogram and scatter plot of capital and labor income Pareto exponents.

only sporadically in the LIS database, we do as follows. First, we consider only the countries that appear in ten or more years in the database. There are eleven such countries, namely: Australia, Canada, Chile, Germany, Israel, Italy, Mexico, Spain, Taiwan, United Kingdom, and United States. Second, for each of these countries, we linearly interpolate the capital and labor Pareto exponents for all years from the available years. (We extrapolate by constants outside the range using the first and last observation year.) Finally, for each year we compute the median Pareto exponent across countries. Figure 2 shows the evolution of capital and labor income Pareto exponents over half a century (1967–2016). We observe that (i) the labor income Pareto exponent decreased from about 3.5 to around 3 over the decade of 1990-2000, but (ii) the capital income Pareto exponent has been stable at slightly below 2. Again, capital income appears to be more unequally distributed than the labor income.

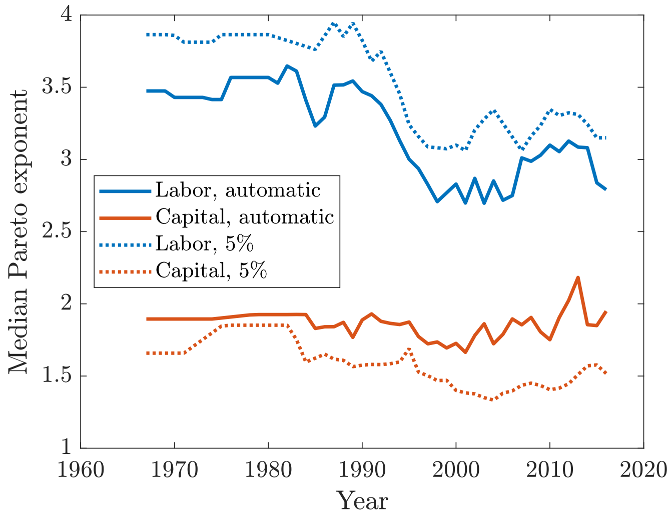



Figure 2: Time evolution of capital and labor income Pareto exponents.

## 2.3 Testing equality of capital and labor Pareto exponents

We now formally test whether the capital and labor Pareto exponents are equal. In particular our test is

$$H_0 : \alpha_{\text{lab}} = \alpha_{\text{cap}} \quad \text{against} \quad H_1 : \alpha_{\text{lab}} \neq \alpha_{\text{cap}},$$

where $\alpha_{\text{cap}}, \alpha_{\text{lab}}$ denote the capital and labor income Pareto exponents. Testing the null hypothesis $H_0$ is complicated by the fact that there is dependency between labor income $\{X_{\text{lab},n}\}_{n=1}^{N}$ and capital income $\{X_{\text{cap},n}\}_{n=1}^{N}$, because individuals who are rich (receive high labor income) tend to be wealthy and receive high capital income. Therefore, we apply the test recently developed by Hoga (2018), which allows for weak dependence in the data. The test is based upon the inverse of the Hill estimator (2.2), which we denote by $\widehat{\gamma} \coloneqq 1/\widehat{\alpha}$. The test statistic is defined by

$$T_N = \frac{(\widehat{\gamma}_{\text{lab}}(1) - \widehat{\gamma}_{\text{cap}}(1))^2}{\int_{t_0}^{1} t^2 \left[(\widehat{\gamma}_{\text{lab}}(t) - \widehat{\gamma}_{\text{cap}}(t)) - (\widehat{\gamma}_{\text{lab}}(1) - \widehat{\gamma}_{\text{cap}}(1))\right]^2 \mathrm{d}t}, \tag{2.5}$$

where $t_0 \in (0, 1)$ is a tuning parameter and $\widehat{\gamma}(t)$ is the inverse Hill estimator

$$\widehat{\gamma}(t) \coloneqq \frac{1}{\lfloor kt \rfloor} \sum_{n=1}^{\lfloor kt \rfloor} \log\left(\frac{X_{n:\lfloor Nt \rfloor}}{X_{\lfloor kt \rfloor:\lfloor Nt \rfloor}}\right). \tag{2.6}$$

Using the Hill estimator based on the subsample with only $\lfloor Nt \rfloor$ observations leads to self-normalization of the test statistic $T_N$ and renders a test that is asymptotically pivotal. The limiting distribution is

$$T_N \xrightarrow{\mathrm{d}} \frac{W(1)^2}{\int_{t_0}^{1} [W(t) - tW(1)]^2 \,\mathrm{d}t}, \tag{2.7}$$

where $W(t)$ is a standard Brownian motion. Note that since the test statistic (2.5) can be computed using only the Hill estimator and conducting numerical integration, there is no need to estimate the (potentially difficult) tail covariance. The tuning parameter $t_0$ affects the size of the test: high values of $t_0$ make the integral in (2.5) based on too few differences of $\widehat{\gamma}$, whereas low values of $t_0$ yield volatile $\widehat{\gamma}$ in (2.6) when $t$ is close to $t_0$. Both of these effects may cause size distortions. Therefore we set $t_0 = 0.2$ following the recommendation of Hoga (2018), who finds that this choice leads to favorable size properties. According to Table I of Hoga (2018), the 95 percentile of (2.7) for $t_0 = 0.2$ is 55.44, which we use as the critical value for testing $H_0$ at 5% significance level.

One issue with the test statistic (2.5) is that it requires the same number of tail observations $k$ for both cross-sections of capital and labor income. Hence the automated selection procedure discussed in Section 2.1 is not applicable because in general we have $k^*_{\text{lab}} \neq k^*_{\text{cap}}$. Furthermore, these two numbers can be substantially different because our observations of capital income contain many zeros (many households do not hold liquid financial wealth and hence have no capital income). The resulting test may thus not be robust since the optimal $k^*_{\text{lab}}$ is wildly different from $k^*_{\text{cap}}$. To overcome this issue, we only test the equality of Pareto exponents for countries that have more than 1,000 positive capital income observations and set $k = \lfloor 0.05N \rfloor$, where $N$ is the number of positive capital income observations. This sample selection results in 245 country-year observations out of 348. Table 3 in Appendix C shows the test results.

We reject the null hypothesis $H_0 : \alpha_{\text{lab}} = \alpha_{\text{cap}}$ in 208 country-year observations out of 245 (84.9%) that meet our sample selection criterion. In every single case of rejection, we have $\widehat{\alpha}_{\text{lab}} > \widehat{\alpha}_{\text{cap}}$, and therefore we formally confirm the observation in Section 2.2 that capital income is more unequally distributed than labor income.

# 3 A simple model of capital and labor Pareto exponents

Our empirical analysis in Section 2 suggests that (i) the capital income Pareto exponent is smaller than the labor one (i.e., capital income is more unequally distributed than labor income), and (ii) the correlation between capital and labor income Pareto exponents is weak. To explain these empirical findings, we present a simple dynamic model of consumption and savings.

## 3.1 Income fluctuation problem

Time is discrete and denoted by $t = 0, 1, 2, \dots$. Let $a_t$ be the financial wealth of a typical agent at the beginning of period $t$ including current income. The agent chooses consumption $c_t \geq 0$ and saves the remaining wealth $a_t - c_t$. The period utility function is $u$, the discount factor is $\beta > 0$, and the gross return on wealth and non-financial income in period $t$ are denoted by $R_t, Y_t > 0$. Thus the agent solves

$$\begin{aligned}
&\text{maximize} && \mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t) && \text{(3.1a)}\\
&\text{subject to} && a_{t+1} = R_{t+1}(a_t - c_t) + Y_{t+1}, && \text{(3.1b)}\\
& && 0 \leq c_t \leq a_t, && \text{(3.1c)}
\end{aligned}$$

where the initial wealth $a_0 = a > 0$ is given, (3.1b) is the budget constraint, and (3.1c) implies that the agent cannot borrow (which is without loss of generality according to the discussion in Chamberlain and Wilson, 2000).

Throughout the rest of the paper we maintain the following assumptions.

**Assumption 1** (CRRA utility)**.** *The utility function exhibits constant relative risk aversion (CRRA) with coefficient* $\gamma > 0$*, so* $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ *if* $\gamma \neq 1$ *and* $u(c) = \log c$ *if* $\gamma = 1$*.*

**Assumption 2** (I.i.d. shocks)**.** *Let* $G_{t+1} := Y_{t+1}/Y_t$ *be the income growth. The sequence* $\{R_{t+1}, G_{t+1}\}_{t=0}^{\infty}$ *is independent and identically distributed (i.i.d.).*

These assumptions are similar to Carroll (2020), except that we allow for stochastic returns on savings. Note that the asset return $R_{t+1}$ and income growth $G_{t+1}$ are potentially mutually dependent. Due to the i.i.d. assumption 2, the state variables of the income fluctuation problem (3.1) are financial wealth $a_t > 0$ and current income $Y_t > 0$. Exploiting homotheticity (Assumption 1), we can reduce the number of state variables to just one, namely the wealth-income ratio (normalized wealth) $\tilde{a}_t := a_t/Y_t$. To see this, letting $\tilde{c}_t := c_t/Y_t$ be the consumption-income ratio (normalized consumption), dividing the borrowing constraint (3.1c) by $Y_t$, we obtain $0 \leq \tilde{c}_t \leq \tilde{a}_t$. Similarly, dividing the budget constraint (3.1b) by $Y_{t+1}$, we obtain

$$\begin{aligned} \tilde{a}_{t+1} = a_{t+1}/Y_{t+1} &= (R_{t+1}Y_t/Y_{t+1})(a_t/Y_t - c_t/Y_t) + 1 \\ &= (R_{t+1}/G_{t+1})(\tilde{a}_t - \tilde{c}_t) + 1 \\ &= \tilde{R}_{t+1}(\tilde{a}_t - \tilde{c}_t) + 1, \end{aligned} \tag{3.2}$$

where $\tilde{R}_{t+1} := R_{t+1}/G_{t+1}$ is the asset return relative to income growth. As for the utility function, since

$$c_t = Y_t \tilde{c}_t = Y_0 \left( \prod_{s=1}^{t} G_s \right) \tilde{c}_t,$$

(here we interpret $\prod_{s=1}^{0} \bullet = 1$) assuming $Y_0 = 1$ (which is without loss of generality) and $\gamma \neq 1$, it follows from (3.1a) that

$$\begin{aligned} \mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t) &= \mathrm{E}_0 \sum_{t=0}^{\infty} \left( \prod_{s=1}^{t} \beta G_s^{1-\gamma} \right) \frac{\tilde{c}_t^{1-\gamma}}{1-\gamma} \\ &= \mathrm{E}_0 \sum_{t=0}^{\infty} \left( \prod_{s=1}^{t} \tilde{\beta}_s \right) \frac{\tilde{c}_t^{1-\gamma}}{1-\gamma}, \end{aligned} \tag{3.3}$$

where $\tilde{\beta}_t := \beta G_t^{1-\gamma}$. The discussion for $\gamma = 1$ is similar. Therefore the problem reduces to an income fluctuation problem with CRRA utility, random discount factors $\left\{ \tilde{\beta}_t \right\}_{t=1}^{\infty}$, stochastic returns $\left\{ \tilde{R}_t \right\}_{t=1}^{\infty}$ on wealth, and constant income ($\tilde{Y}_t \equiv 1$). The general theory of income fluctuation problems with stochastic discounting, returns, and income in a Markovian setting was developed by Ma et al. (2020). Therefore we immediately obtain the following result.

**Proposition 1.** *Suppose Assumptions 1, 2 hold and*

$$\beta \, \mathrm{E} \, G^{1-\gamma} < 1 \quad \textit{and} \quad \beta \, \mathrm{E} \, R G^{-\gamma} < 1. \tag{3.4}$$

*Then the income fluctuation problem (3.1) has a unique solution. The consumption function can be expressed as*

$$c(a, Y) = Y \tilde{c}(a/Y),$$

*where $\tilde{c} : (0, \infty) \to (0, \infty)$ is the consumption function of the detrended problem (maximizing (3.3) subject to (3.2)), which can be computed by policy function iteration.*[5]

*Proof.* Applying Theorem 2.2 of Ma et al. (2020) to the i.i.d. case, a sufficient condition for the existence of a solution to the detrended problem is $\mathrm{E}\,\tilde{\beta} < 1$ and $\mathrm{E}\,\tilde{\beta}\tilde{R} < 1$, which is equivalent to (3.4). □

## 3.2 Tail behavior of income and wealth

We now characterize the tail behavior of income and wealth in the context of the income fluctuation problem in Section 3.1.

To make the model stationary, suppose that agents survive to the next period with probability $\upsilon \in (0, 1)$ (perpetual youth model as in Yaari, 1965). Whenever agents die, they are replaced by newborn agents. For simplicity, assume that the discount factor $\beta$ in (3.1a) already accounts for survival probability and that there is no market for life insurance (allowing for life insurance only changes $R$ to $R/\upsilon$ and is thus mathematically equivalent after reparametrization). Without loss of generality, suppose that newborn agents start with income $Y_0 = 1$. Then the income of a randomly selected agent is $Y_T$, where $T$ is a geometric random variable with mean $\frac{1}{1-\upsilon}$. By the assumption on income growth, the log income of a randomly selected agent

$$\log Y_T = \log(Y_T/Y_0) = \sum_{t=1}^{T} \log G_t$$

[5] See Li and Stachurski (2014) and Ma et al. (2020) for details on policy function iteration.

is a geometric sum of i.i.d. random variables, for which we can characterize the tail behavior as follows.

**Proposition 2** (Income Pareto exponent)**.** *Suppose that* $\mathrm{P}(G > 1) > 0$ *and* $1 < v \mathrm{E}\, G^z < \infty$ *for some* $z > 0$*. Then the cross-sectional income distribution has a Pareto upper tail with exponent* $\alpha_Y$*, which is the unique positive solution to*

$$v \mathrm{E}\, G^z = 1. \tag{3.5}$$

*Proof.* See Beare and Toda (2017, Theorem 3.4). □

Characterizing the tail behavior of wealth is more difficult. We first note that the normalized consumption function $\tilde{c}$ in Proposition 1 is asymptotically linear.

**Proposition 3** (Asymptotic linearity)**.** *Let everything be as in Proposition 1. Then*

$$\lim_{a \to \infty} \frac{\tilde{c}(a)}{a} = \begin{cases} 1 - (\mathrm{E}\, \beta R^{1-\gamma})^{1/\gamma} & \text{if } \mathrm{E}\, \beta R^{1-\gamma} < 1, \\ 0 & \text{otherwise.} \end{cases} \tag{3.6}$$

*Proof.* The asymptotic linearity of $\tilde{c}$ follows from Ma and Toda (2020, Theorem 2.2). Noting that

$$\mathrm{E}\, \tilde{\beta} \tilde{R}^{1-\gamma} = \mathrm{E}\, \beta G^{1-\gamma} (R/G)^{1-\gamma} = \mathrm{E}\, \beta R^{1-\gamma},$$

the limit (3.6) follows from their Example 2.2. □

Using Proposition 3 and setting $\rho = \min\left\{(\mathrm{E}\, \beta R^{1-\gamma})^{1/\gamma}, 1\right\}$, for high enough asset level, the detrended budget constraint (3.2) becomes approximately

$$\tilde{a}_{t+1} \approx \rho \tilde{R}_{t+1} \tilde{a}_t + 1,$$

which is a random growth process. Under specific assumptions, Ma et al. (2020, Theorem 3.3) prove that the upper tail of the stationary distribution of normalized wealth $\tilde{a}_t$ has a Pareto lower bound. Although a sharp characterization of the tail behavior is a difficult open problem, we proceed heuristically following the discussion of Toda (2019) and conjecture that the Beare and Toda (2017) formula is applicable in this setting. Hence we obtain the following result.

**Claim.** *Let* $\rho = \min \left\{ (\mathrm{E}\, \beta R^{1-\gamma})^{1/\gamma}, 1 \right\}$ *and* $H = \rho \tilde{R}$. *Suppose that* $\mathrm{P}(H > 1) > 0$ *and* $1 < v \, \mathrm{E}\, H^z < \infty$ *for some* $z > 0$. *Then the cross-sectional normalized wealth distribution has a Pareto upper tail with exponent* $\tilde{\alpha}$, *which is the unique positive solution of*

$$v \, \mathrm{E}\, H^z = 1. \tag{3.7}$$

*The Pareto exponent for wealth and capital income is then* $\alpha = \min \{\tilde{\alpha}, \alpha_Y\}$.

*Proof.* By accounting, capital income (excluding capital loss) is

$$Y_{\text{cap}} := \max \{R - 1, 0\} (a - c(a)) = \max \{R - 1, 0\} Y (\tilde{a} - \tilde{c}(\tilde{a})).$$

Using Proposition 3, this quantity is approximately equal to $\rho \max \{R - 1, 0\} Y \tilde{a}$. The claim $\alpha = \min \{\tilde{\alpha}, \alpha_Y\}$ then follows because asset return $R$ is thin-tailed under the assumption $v \, \mathrm{E}\, H^z < \infty$ and $a_t = Y_t \tilde{a}_t$ is the product of two (potentially dependent) random variables with Pareto upper tails, which inherits the smallest Pareto exponent by the result in Jessen and Mikosch (2006). $\square$

**Remark.** The normalized wealth Pareto exponent $\tilde{\alpha}$, which solves (3.7), generally depends on both asset return $R$ and income growth $G$ because $H = \rho\tilde{R} = \rho R/G$. This does not contradict the result of Stachurski and Toda (2019) because income is stationary in their setting, whereas by Assumption 2 income exhibits random growth in our model.

We discuss an analytically solvable example to build intuition.

**Example 1.** Let $\Delta > 0$ be the length of time of one period and the discount factor be $\beta = \mathrm{e}^{-\delta\Delta}$, where $\delta > 0$ is the discount rate. Suppose income grows at a constant rate $g > 0$, so $G = \mathrm{e}^{g\Delta}$. Suppose asset return is risk-free, so $R = \mathrm{e}^{r\Delta}$ with $r > 0$. Finally, let the survival probability be $v = \mathrm{e}^{-\eta\Delta}$, where $\eta$ is the death rate. Then (3.5) becomes

$$1 = \mathrm{e}^{-\eta\Delta}\mathrm{e}^{zg\Delta} \iff z = \eta/g,$$

so the income Pareto exponent is $\alpha_Y = \eta/g$. (This is the classical result of Wold and Whittle (1957) in discrete-time.) Suppose in addition that $-\eta + r(1-\gamma) < 0$ so that $\beta R^{1-\gamma} < 1$. Since

$$H = (\mathrm{E}\,\beta R^{1-\gamma})^{1/\gamma}\tilde{R} = (\beta R)^{1/\gamma}/G = \mathrm{e}^{(\frac{r-\eta}{\gamma}-g)\Delta},$$

solving (3.7) the normalized wealth Pareto exponent is

$$\tilde{\alpha} = \frac{\eta\gamma}{r - \eta - g\gamma}$$

assuming $r - \eta - g\gamma > 0$. Therefore

$$\tilde{\alpha} < \alpha_Y \iff \frac{\eta\gamma}{r - \eta - g\gamma} < \frac{\eta}{g} \iff r > \eta + 2g\gamma,$$

so the wealth (hence capital income) Pareto exponent is smaller than the labor income Pareto exponent if the return on wealth $r$ is sufficiently large. In summary, we obtain the following result: suppose $-\eta + r(1-\gamma) < 0$ and let $\alpha_{\text{cap}}, \alpha_{\text{lab}}$ be the capital and labor income Pareto exponents. Then

$$\begin{cases} \alpha_{\text{cap}} = \alpha_{\text{lab}} = \frac{\eta}{g} & \text{if } r \le \eta + 2g\gamma, \\ \alpha_{\text{cap}} = \frac{\eta\gamma}{r-\eta-g\gamma} < \frac{\eta}{g} = \alpha_{\text{lab}} & \text{if } r > \eta + 2g\gamma. \end{cases} \tag{3.8}$$

Note that the labor income Pareto exponent $\alpha_{\text{lab}} = \eta/g$ is highly sensitive to the income growth rate $g$. However, provided that $r > \eta + 2g\gamma$, the capital income Pareto exponent $\alpha_{\text{cap}}$ is not very sensitive to the value of $g$ because the denominator is $r - \eta - g\gamma$. This example is consistent with our result in Section 2.2 that the capital Pareto exponent is smaller than the labor Pareto exponent but the two values are only weakly related.

## 3.3 Numerical example

We further examine the tail behavior of income and wealth using a numerical example of the income fluctuation problem (3.1). Suppose that asset return is i.i.d. lognormal, so $\log R \sim N((\mu - \sigma^2/2)\Delta, \sigma^2\Delta)$, where $\Delta > 0$ is the length of one period, $\mu$ is the expected return, and $\sigma$ is volatility. Suppose every period the agent is "promoted" with some probability, so the income growth rate is

$$G_{t+1} = Y_{t+1}/Y_t = \begin{cases} 1 & \text{with probability } 1-p, \\ \mathrm{e}^g & \text{with probability } p, \end{cases}$$

where $p \in (0,1)$ is the promotion probability and $g$ is the log income growth rate conditional on promotion. We parametrize the promotion probability as $p = 1 - \mathrm{e}^{-\Delta/L}$, where $L$ is the expected length of time until a promotion. Using (3.5), the labor income Pareto exponent is determined such that

$$1 = v \, \mathrm{E}\, G^{\alpha_Y} = v(1 - p + p\mathrm{e}^{g\alpha_Y}) \iff \alpha_Y = \frac{1}{g} \log \frac{1 - v + vp}{vp}. \tag{3.9}$$

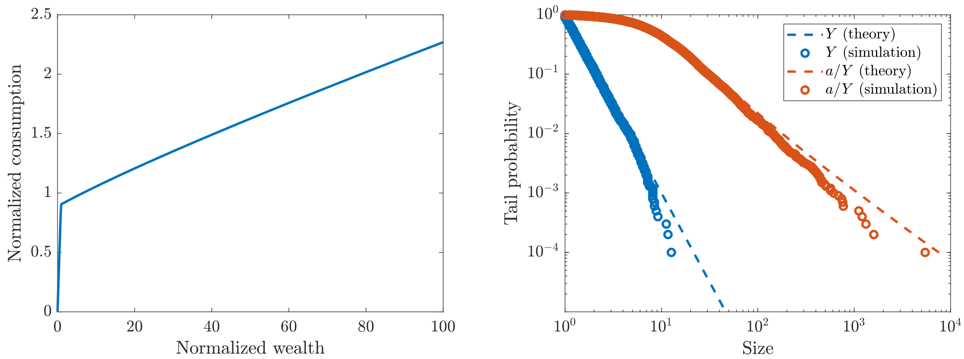
We set the parameter values as in Table 1. One unit of time corresponds to a year and one period is a quarter, so $\Delta = 1/4$. The preference parameters (discount rate and risk aversion) are standard. The death rate of $\eta = 0.025$ implies an average (economically active) age of $1/\eta = 40$ years. The expected return and volatility roughly correspond to the stock market. We set the labor income Pareto exponent to $\alpha_Y = 3$, which is roughly the median value in Figure 1. Using the survival probability $v = \mathrm{e}^{-\eta\Delta}$ and (3.9), the implied value of income growth upon promotion is $g = 0.0403$. The wealth Pareto exponent determined by (3.7) is then $\alpha = 1.201$.

To numerically solve the income fluctuation problem (3.1), we discretize the log asset return $\log R$ using a 7-point Gauss-Hermite quadrature and apply policy function iteration (see Appendix B). After solving the individual problem, we apply the Pareto extrapolation algorithm developed in Gouin-Bonenfant and Toda (2018) to accurately compute the stationary (normal-

Table 1: Parameter values

| Parameter | Symbol | Value |
|---|---|---|
| Length of one period | $\Delta$ | 1/4 |
| Discount rate | $\delta$ | 0.04 |
| Relative risk aversion | $\gamma$ | 2 |
| Death rate | $\eta$ | 0.025 |
| Expected return | $\mu$ | 0.07 |
| Volatility | $\sigma$ | 0.15 |
| Expected time to promotion | $L$ | 5 |
| Labor income Pareto exponent | $\alpha_Y$ | 3 |

ized) wealth distribution. Finally, we also simulate an economy with $10^4$ agents. Figure 3 shows the results.




(a) Normalized consumption function. (b) Income and wealth distributions.

Figure 3: Solution to income fluctuation problem.

Figure 3a shows the normalized consumption function $\tilde{c}(\tilde{a})$ in the range $\tilde{a} \in [0, 100]$. Consistent with Proposition 3, the consumption function is roughly linear for high asset level. Figure 3b shows the size distributions of income $Y$ normalized wealth $\tilde{a} = a/Y$ in a log-log plot, both from the theoretical model and the simulation. The fact that the tail probability $\mathrm{P}(X > x)$ exhibits a straight line pattern in a log-log plot suggests that the size distributions have Pareto upper tails, consistent with theory. Furthermore, the slope for income is steeper than that of normalized wealth, so wealth (hence capital income) is more unequally distributed than labor income.

Finally, Figure 4 shows the income and wealth Pareto exponents when we change the income growth rate $g$ in the range $g \in [0.02, 0.1]$, fixing other parameters. Because the income Pareto exponent is inversely proportional to income growth by (3.9), the labor income Pareto exponent is highly sensitive to income growth. On the other hand, the wealth (capital income) Pareto exponent does not depend much on income growth by the same intuition as in Example 1. Thus our model is consistent with our empirical findings in Section 2.2 that capital and labor income Pareto exponents are only weakly related.

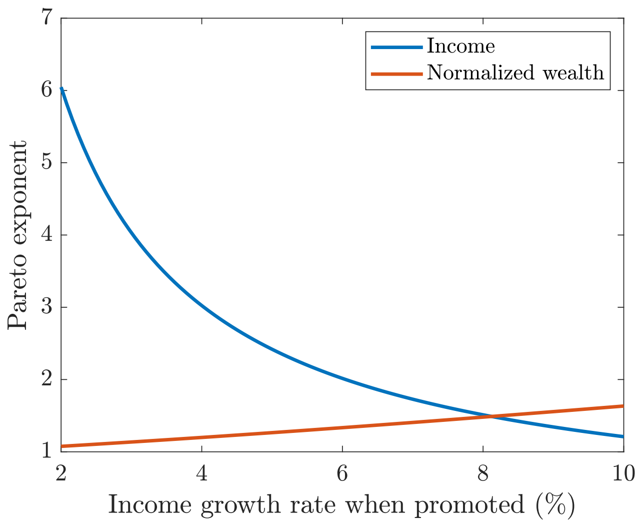



Figure 4: Dependence of income and wealth Pareto exponents on $g$.

## 3.4 Determinants of inequality

This section examines the relation between our estimated Pareto exponents $\alpha$ for capital and labor income and explanatory variables based on our model in Section 3.2.

**Data** We obtain regressors from two main sources: *Penn World Table*[6] and *World Bank*.[7] We construct the GDP growth rate series ($g$) based real GDP per capita expressed in current U.S. dollars. In addition, we use the number of deaths per 1,000 population as a proxy for the death rate ($\eta$). Finally, we use the internal rate of return ($r$) from the Penn World Table as a proxy for the return on capital. Since our panel consisting of estimated $\alpha$ is highly unbalanced, we average all covariates over a five-year rolling window to smooth their effect over time.

**Results** We use a fixed effect panel regression approach to estimate our model, which allows the fixed effects to be correlated with the explanatory variables. This is important in our context, since there might be underlying forces specific to a country (e.g., culture) that correlate with economic growth, mortality rate, and other factors (see also Acemoglu et al. (2008) for a similar context). The regressions for labor and capital income are reported in (3.10a) and (3.10b), respectively. Standard errors (in parentheses) are heteroskedasticity-robust and clustered by country to account for possible

[6] https://www.rug.nl/ggdc/productivity/pwt/

[7] https://data.worldbank.org/

dependency of the error terms within countries over time.

$$\widehat{\alpha}_{\mathrm{lab},it} = \underset{(0.746)}{2.475} + \underset{(1.182)}{1.623} g_{it} - \underset{(3.251)}{6.275} r_{it} + \underset{(0.067)}{0.112} \eta_{it} + \varepsilon_{it}, \tag{3.10a}$$

$$\widehat{\alpha}_{\mathrm{cap},it} = \underset{(0.894)}{1.514} + \underset{(0.768)}{0.949} g_{it} - \underset{(2.280)}{0.892} r_{it} + \underset{(0.071)}{0.028} \eta_{it} + \varepsilon_{it}. \tag{3.10b}$$

Since we set the average fixed effect to zero, the intercept can be interpreted as the mean Pareto exponent. Hence, the panel regression confirms our earlier finding that capital income is more unequal than labor income. Only the $r$ and $\eta$ coefficients are significant at 10% level and other coefficients (except the intercept) are insignificant. The fact that the labor income Pareto exponent $\alpha_{\mathrm{lab}}$ is positively related with the death rate $\eta$ in (3.10a) is consistent with the model, see for example (3.8). Although the $g$ coefficient in (3.10a) is insignificant, it has the correct sign. The fact that $\alpha_{\mathrm{lab}}$ is negatively related to the return $r$ in (3.10a) is not predicted by theory.

Overall, the panel regression result is uninformative about the determinants of inequality. Although the coefficients have the correct signs, most of them are insignificant possibly due to the limited sample size. In addition, these regressions document only correlation and abstract from endogeneity problems. We view our results as predictive in nature and leave the causal inference for future research.

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# A Data

In this Appendix we describe the dataset that we use and discuss its limitations.

## A.1 The LIS database

We use the data from the *Luxembourg Income Study* (LIS), which is a large, harmonized database of micro-level income data that covers about 50 countries worldwide and many years since the late 1960s. In many countries, the data derive from government surveys (for example, the U.S. data is based on the *Current Population Survey*). The LIS data are available at both individual and household level. We focus on the household labor and capital income because (i) it is reasonable to assume that economic decisions such as financial planning are made at the household level, and (ii) incomes among couples are likely correlated due to assortative matching in the marriage market (Siow, 2015), which invalidates statistical estimation.[8] The LIS defines *labor income* as "cash payments and value of goods and services received from dependent employment, as well as profits/losses and value of goods from self-employment, including own consumption". *Capital income* is defined as "cash payments from property and capital (including financial and non-financial assets), including interest and dividends, rental income and royalties, and other capital income from investment in self-employment activity". Together these two categories make up total *factor income*. See the LIS 2019 USER GUIDE[9] for a detailed summary on how these data are retrieved and calculated.

## A.2 Data limitations

Our analysis draws upon datasets from many different countries that are harmonized into a common framework by LIS. However, many details about the collection of data in the different countries are omitted. For example, we find evidence of top-coding in some countries and years, as the largest income order statistic is equal to the second largest.[10] Top-coding induces an upward bias in the estimation of the Pareto exponent. This issue is not necessarily resolved if, instead, one relies on administrative tax income data, for similar biases arise such as rich households trying to understate their taxable income

[8] In our data, we find an average correlation of 0.22 between labor income of husband and wife, which underpins the conjectured dependency.

[9] https://www.lisdatacenter.org/wp-content/uploads/files/data-lis-guide.pdf

[10] Among all 348 country-year observations, the first and second order statistics are equal in 2 cases for labor income and 7 cases for capital income. Therefore we conjecture that the top-coding issue is not severe.

(Atkinson et al., 2011). Burkhauser et al. (2012) detail a method that can be used to overcome the bias due to top-coding, however at the end of their paper they show that the results are robust even if estimates are based on the top-coded series. For these reasons we treat the datasets as not being top-coded in our analysis.

Another limitation of the LIS database is that it is based on government surveys and the measurement error may be larger compared to administrative data based on tax returns. The fact that the income distribution in administrative data is often reported as tabulations, not micro data, causes no problem for estimating Pareto exponents, as Toda and Wang (2020) provide an efficient estimation method for such data. In fact, Atkinson and Piketty (2010, Table 13A.23) document income Pareto exponents across countries and years estimated from top income share data. However, their table is based on total income, and since (as we document in Section 2.3) the capital income Pareto exponents tend to be smaller than labor exponents, the estimates in Atkinson and Piketty (2010) are best understood as capital income (hence wealth) Pareto exponents. Since we are not aware of a comprehensive income database that distinguishes capital and labor income, we decided to use the LIS database.

# B Solving the income fluctuation problem

In this appendix we discuss how to solve the detrended income fluctuation problem. After detrending, the problem becomes

$$\begin{aligned} &\text{maximize} && \mathrm{E}_0 \sum_{t=0}^{\infty} \left( \prod_{s=1}^{t} \beta_t \right) \frac{c_t^{1-\gamma}}{1-\gamma} \\ &\text{subject to} && a_{t+1} = R_{t+1}(a_t - c_t) + 1, \\ &&& 0 \le c_t \le a_t, \end{aligned}$$

where $\{R_t, \beta_t\}_{t=1}^{\infty}$ is i.i.d. (though $R_t$ and $\beta_t$ are generally correlated.) According to Ma et al. (2020), the Euler equation is

$$c_t^{-\gamma} = \max \left\{ \mathrm{E}_t \, \beta_{t+1} R_{t+1} c_{t+1}^{-\gamma}, a_t^{-\gamma} \right\}. \tag{B.1}$$

Let $c(a)$ be the consumption function. Taking the $-1/\gamma$-th power of (B.1), we obtain

$$c(a) = \min \left\{ \left[ \mathrm{E} \, \beta R c(a')^{-\gamma} \right]^{-1/\gamma}, a \right\}, \tag{B.2}$$

where $a' = R(a - c(a)) + 1$. Therefore we can compute the consumption function using the following variant of the policy function iteration algorithm:

1. Initialize the consumption function $c(a)$. For example, we can set $c(a) = \min \{a, 1 + ma\}$, where $m = \max \left\{ 1 - (\mathrm{E} \, \beta R^{1-\gamma})^{1/\gamma}, 0 \right\}$ is the theoretical asymptotic marginal propensity to consume according to (3.6).

2. Update $c(a)$ by the right-hand side of (B.2), where $a' = R(a - c(a)) + 1$.

3. Iterate the above step until $c(a)$ converges.

While the above algorithm has no guarantee to converge unlike the "true" policy function iteration algorithm discussed in Ma et al. (2020), it has the advantage of avoiding root-finding and hence it is fast.

In Section 3, we use this algorithm on a 100-point exponential grid for normalized wealth $\tilde{a}$ that spans $[0, 10^4]$, with a median grid point of 10. The details on the exponential grid are discussed in Gouin-Bonenfant and Toda (2018).

# C Tables

Table 2: Point estimates of income Pareto exponents across countries and years.

| | | Labor income | | | | Capital income | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | Year | $\widehat{\alpha}$ | s.e. | $k$ | $N$ | $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
| Australia | 1981 | 5.25 | 0.24 | 463 | 10568 | 2.9 | 0.3 | 96 | 9488 |
| Australia | 1985 | 3.23 | 0.41 | 61 | 5492 | 1.79 | 0.2 | 81 | 5232 |
| Australia | 1989 | 3.7 | 0.12 | 1034 | 10629 | 1.98 | 0.19 | 111 | 10973 |
| Australia | 1995 | 2.92 | 0.29 | 99 | 4574 | 1.82 | 0.15 | 153 | 3364 |
| Australia | 2001 | 3.62 | 0.53 | 46 | 4510 | 1.52 | 0.13 | 132 | 3105 |
| Australia | 2003 | 2.66 | 0.29 | 86 | 6741 | 1.86 | 0.17 | 122 | 4473 |
| Australia | 2004 | 3.49 | 0.13 | 739 | 7893 | 1.72 | 0.14 | 162 | 6145 |
| Australia | 2008 | 2.99 | 0.15 | 411 | 6666 | 1.41 | 0.12 | 141 | 4749 |
| Australia | 2010 | 3.58 | 0.31 | 137 | 10949 | 1.44 | 0.08 | 296 | 9030 |
| Australia | 2014 | 2.79 | 0.23 | 146 | 9788 | 1.29 | 0.07 | 365 | 9569 |
| Austria | 1994 | 3.46 | 0.25 | 197 | 2183 | 1.52 | 0.13 | 131 | 1693 |
| Austria | 1997 | 3.55 | 0.41 | 74 | 1998 | 1.84 | 0.14 | 173 | 1787 |
| Austria | 2000 | 3.08 | 0.33 | 88 | 1584 | 3.37 | 0.72 | 22 | 1547 |
| Austria | 2004 | 3.57 | 0.31 | 134 | 3749 | 1.73 | 0.26 | 45 | 4064 |
| Austria | 2007 | 3.3 | 0.2 | 269 | 4101 | 1.51 | 0.22 | 48 | 4334 |
| Austria | 2010 | 3.61 | 0.35 | 106 | 4323 | 1.54 | 0.19 | 65 | 4752 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| | | Labor income | | | | Capital income | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | Year | $\widehat{\alpha}$ | s.e. | $k$ | $N$ | $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
| Austria | 2013 | 3.25 | 0.17 | 378 | 4022 | 1.38 | 0.18 | 60 | 4471 |
| Belgium | 1985 | 4.81 | 0.7 | 47 | 4357 | 3.14 | 0.64 | 24 | 397 |
| Belgium | 1988 | 3.39 | 0.64 | 28 | 2518 | 1.58 | 0.37 | 18 | 332 |
| Belgium | 1992 | 4.69 | 0.33 | 202 | 2581 | 2.11 | 0.36 | 35 | 349 |
| Belgium | 1995 | 2.93 | 0.43 | 46 | 1790 | 3.1 | 0.42 | 54 | 893 |
| Belgium | 1997 | 4 | 0.24 | 288 | 2906 | 3.06 | 0.44 | 48 | 4112 |
| Belgium | 2000 | 1.93 | 0.5 | 15 | 1431 | 0.9 | 0.32 | 8 | 715 |
| Brazil | 2006 | 2.77 | 0.08 | 1122 | 99559 | 2.16 | 0.2 | 119 | 9594 |
| Brazil | 2009 | 2.35 | 0.05 | 2045 | 100002 | 1.4 | 0.04 | 1081 | 19059 |
| Brazil | 2011 | 2.68 | 0.09 | 947 | 89066 | 1.93 | 0.14 | 198 | 19291 |
| Brazil | 2013 | 2.74 | 0.09 | 955 | 91657 | 1.77 | 0.1 | 340 | 21092 |
| Canada | 1971 | 4 | 0.11 | 1239 | 20386 | 2.48 | 0.22 | 129 | 9970 |
| Canada | 1975 | 4.13 | 0.22 | 344 | 21750 | 2.47 | 0.21 | 134 | 10717 |
| Canada | 1981 | 5.18 | 0.41 | 158 | 12331 | 2.54 | 0.28 | 85 | 8342 |
| Canada | 1987 | 4.5 | 0.48 | 89 | 8667 | 2.29 | 0.21 | 118 | 5190 |
| Canada | 1991 | 3.59 | 0.29 | 154 | 15257 | 2.51 | 0.17 | 223 | 9847 |
| Canada | 1994 | 3.56 | 0.21 | 283 | 28155 | 2.31 | 0.19 | 154 | 14077 |
| Canada | 1997 | 3.75 | 0.08 | 2385 | 25018 | 1.53 | 0.05 | 1117 | 11273 |
| Canada | 1998 | 2.71 | 0.17 | 241 | 23969 | 1.74 | 0.15 | 143 | 13486 |
| Canada | 2000 | 2.89 | 0.19 | 225 | 22298 | 1.53 | 0.06 | 624 | 13264 |
| Canada | 2004 | 2.85 | 0.18 | 239 | 21594 | 2.05 | 0.13 | 244 | 11861 |
| Canada | 2007 | 2.45 | 0.15 | 260 | 20918 | 1.96 | 0.16 | 150 | 12533 |
| Canada | 2010 | 3.32 | 0.08 | 1866 | 19500 | 2.3 | 0.19 | 149 | 10341 |
| Canada | 2013 | 4.1 | 0.29 | 194 | 18069 | 2.5 | 0.25 | 102 | 9741 |
| Chile | 1990 | 2.41 | 0.12 | 380 | 22755 | 1.39 | 0.14 | 100 | 1242 |
| Chile | 1992 | 2.39 | 0.12 | 369 | 31934 | 1.86 | 0.31 | 37 | 1678 |
| Chile | 1994 | 1.81 | 0.03 | 3985 | 39851 | 1.78 | 0.13 | 199 | 2071 |
| Chile | 1996 | 2.71 | 0.15 | 323 | 30177 | 1.35 | 0.21 | 40 | 3437 |
| Chile | 1998 | 1.96 | 0.04 | 2317 | 42903 | 1.4 | 0.09 | 254 | 3335 |
| Chile | 2000 | 2.17 | 0.07 | 856 | 57716 | 1.27 | 0.12 | 115 | 4432 |
| Chile | 2003 | 2.08 | 0.05 | 1463 | 60055 | 1.35 | 0.08 | 274 | 4637 |
| Chile | 2006 | 2.46 | 0.09 | 815 | 65111 | 1.32 | 0.06 | 493 | 5374 |
| Chile | 2009 | 2.73 | 0.11 | 642 | 59668 | 2.29 | 0.34 | 45 | 3619 |
| Chile | 2011 | 2.82 | 0.11 | 669 | 50887 | 1.91 | 0.27 | 49 | 3312 |
| Chile | 2013 | 2.59 | 0.11 | 583 | 57079 | 2.2 | 0.29 | 56 | 3635 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| Country | Year | Labor income $\widehat{\alpha}$ | s.e. | $k$ | $N$ | Capital income $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|
| Chile | 2015 | 2.73 | 0.09 | 927 | 69790 | 1.51 | 0.1 | 214 | 5314 |
| China | 2002 | 3.58 | 0.26 | 186 | 16745 | 1.61 | 0.11 | 198 | 2156 |
| China | 2013 | 2.78 | 0.07 | 1588 | 15878 | 1.61 | 0.06 | 825 | 10098 |
| Colombia | 2004 | 1.91 | 0.07 | 779 | 8255 | 1.64 | 0.17 | 99 | 1196 |
| Colombia | 2007 | 1.92 | 0.05 | 1357 | 14298 | 1.57 | 0.15 | 103 | 1961 |
| Colombia | 2010 | 2.26 | 0.08 | 824 | 14705 | 1.3 | 0.09 | 204 | 2037 |
| Colombia | 2013 | 2.83 | 0.22 | 161 | 13986 | 1.38 | 0.11 | 172 | 1983 |
| Czech Rep. | 1992 | 2.94 | 0.23 | 168 | 13287 | 1.13 | 0.2 | 33 | 444 |
| Czech Rep. | 1996 | 3.05 | 0.19 | 270 | 23587 | 1.79 | 0.27 | 43 | 3077 |
| Czech Rep. | 2002 | 3.17 | 0.14 | 502 | 6082 | 2.01 | 0.35 | 33 | 973 |
| Czech Rep. | 2004 | 2.38 | 0.42 | 32 | 3125 | 1.52 | 0.51 | 9 | 729 |
| Czech Rep. | 2007 | 3.33 | 0.12 | 823 | 8254 | 1.27 | 0.17 | 55 | 1735 |
| Czech Rep. | 2010 | 3.64 | 0.17 | 463 | 6551 | 2.29 | 0.5 | 21 | 1422 |
| Czech Rep. | 2013 | 3.18 | 0.13 | 597 | 5996 | 1.34 | 0.17 | 66 | 1198 |
| Denmark | 1987 | 4.18 | 0.29 | 214 | 9199 | 1.44 | 0.05 | 852 | 11575 |
| Denmark | 1992 | 3.75 | 0.38 | 97 | 9164 | 1.3 | 0.05 | 818 | 11853 |
| Denmark | 1995 | 4.41 | 0.06 | 5719 | 57306 | 1.19 | 0.02 | 4704 | 70200 |
| Denmark | 2000 | 4.11 | 0.05 | 5879 | 59549 | 1.3 | 0.03 | 2092 | 69714 |
| Denmark | 2004 | 3.46 | 0.14 | 624 | 59824 | 1.4 | 0.03 | 1853 | 67886 |
| Denmark | 2007 | 3.19 | 0.13 | 614 | 61255 | 1.26 | 0.02 | 2575 | 78755 |
| Denmark | 2010 | 2.6 | 0.11 | 596 | 59488 | 1.13 | 0.02 | 3900 | 69287 |
| Denmark | 2013 | 2.97 | 0.12 | 614 | 60880 | 1.29 | 0.03 | 2012 | 68088 |
| Dominican Rep. | 2007 | 2.9 | 0.31 | 85 | 7471 | 1.18 | 0.27 | 19 | 544 |
| Egypt | 2012 | 1.82 | 0.09 | 380 | 10095 | 1.34 | 0.17 | 65 | 727 |
| Estonia | 2000 | 3.26 | 0.26 | 162 | 5196 | 0.74 | 0.37 | 4 | 206 |
| Estonia | 2004 | 3.72 | 0.36 | 104 | 3116 | 2.85 | 0.82 | 12 | 238 |
| Estonia | 2007 | 3.91 | 0.24 | 271 | 4201 | 1.49 | 0.31 | 23 | 2250 |
| Estonia | 2010 | 4.51 | 0.41 | 122 | 4241 | 1.47 | 0.32 | 21 | 1948 |
| Estonia | 2013 | 4.37 | 0.58 | 57 | 4951 | 1.4 | 0.32 | 19 | 1450 |
| Finland | 1987 | 3.94 | 0.12 | 1120 | 11225 | 1.44 | 0.06 | 627 | 7906 |
| Finland | 1991 | 4.41 | 0.36 | 150 | 10380 | 1.55 | 0.12 | 174 | 8332 |
| Finland | 1995 | 4.02 | 0.42 | 92 | 7867 | 1.28 | 0.19 | 47 | 4236 |
| Finland | 2000 | 2.7 | 0.28 | 91 | 8977 | 1.07 | 0.06 | 314 | 5923 |
| Finland | 2004 | 3.92 | 0.39 | 100 | 9368 | 1.31 | 0.11 | 154 | 8061 |
| Finland | 2007 | 3.61 | 0.15 | 570 | 8664 | 1.46 | 0.15 | 93 | 8502 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| | | Labor income | | | | Capital income | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | Year | $\widehat{\alpha}$ | s.e. | $k$ | $N$ | $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
| Finland | 2010 | 3.64 | 0.13 | 739 | 7537 | 1.16 | 0.09 | 152 | 7571 |
| Finland | 2013 | 3.73 | 0.15 | 601 | 8899 | 1.25 | 0.08 | 257 | 9145 |
| France | 1978 | 2.53 | 0.24 | 113 | 7664 | 1.63 | 0.17 | 91 | 1426 |
| France | 1984 | 4.72 | 0.51 | 84 | 7875 | 1.81 | 0.19 | 90 | 1974 |
| France | 1989 | 3.64 | 0.37 | 95 | 5942 | 1.55 | 0.14 | 125 | 1677 |
| France | 1994 | 2.99 | 0.11 | 738 | 7880 | 1.92 | 0.15 | 162 | 8734 |
| France | 2000 | 3.88 | 0.44 | 79 | 7112 | 1.48 | 0.06 | 556 | 8530 |
| France | 2005 | 3.24 | 0.15 | 495 | 7987 | 1.75 | 0.14 | 147 | 8330 |
| France | 2010 | 2.55 | 0.23 | 119 | 11820 | 2.3 | 0.21 | 124 | 11660 |
| Germany | 1973 | 3.43 | 0.09 | 1470 | 37614 | 2.23 | 0.03 | 4459 | 44891 |
| Germany | 1978 | 2.52 | 0.13 | 392 | 35731 | 2.3 | 0.03 | 4348 | 44654 |
| Germany | 1981 | 3.51 | 0.73 | 23 | 2024 | 2.54 | 0.73 | 12 | 163 |
| Germany | 1983 | 3.79 | 0.2 | 377 | 32288 | 2.47 | 0.12 | 458 | 40130 |
| Germany | 1984 | 2.62 | 0.4 | 43 | 4240 | 1.79 | 0.27 | 45 | 4259 |
| Germany | 1987 | 3.63 | 0.57 | 40 | 3863 | 1.52 | 0.21 | 52 | 4050 |
| Germany | 1989 | 2.68 | 0.43 | 39 | 3733 | 1.54 | 0.18 | 74 | 3940 |
| Germany | 1991 | 4.08 | 0.18 | 508 | 5448 | 1.46 | 0.14 | 117 | 5789 |
| Germany | 1994 | 3.35 | 0.43 | 62 | 5384 | 1.55 | 0.14 | 118 | 5758 |
| Germany | 1995 | 3.96 | 0.17 | 514 | 5275 | 1.3 | 0.07 | 361 | 5802 |
| Germany | 1998 | 4.27 | 0.18 | 551 | 5531 | 1.64 | 0.16 | 102 | 6136 |
| Germany | 2000 | 3.42 | 0.36 | 89 | 8784 | 1.75 | 0.13 | 177 | 9829 |
| Germany | 2001 | 2.7 | 0.28 | 95 | 9273 | 1.38 | 0.08 | 281 | 10174 |
| Germany | 2002 | 3.37 | 0.11 | 882 | 8850 | 1.34 | 0.06 | 436 | 9798 |
| Germany | 2003 | 2.79 | 0.29 | 91 | 8600 | 1.07 | 0.03 | 935 | 9875 |
| Germany | 2004 | 3.38 | 0.12 | 825 | 8300 | 1.1 | 0.04 | 917 | 9544 |
| Germany | 2005 | 2.74 | 0.29 | 90 | 8869 | 1.24 | 0.05 | 516 | 10338 |
| Germany | 2006 | 3.15 | 0.11 | 827 | 8276 | 1.47 | 0.1 | 238 | 9562 |
| Germany | 2007 | 3.14 | 0.35 | 79 | 7778 | 1.17 | 0.05 | 608 | 9055 |
| Germany | 2008 | 2.61 | 0.28 | 89 | 7295 | 1.51 | 0.15 | 103 | 8497 |
| Germany | 2009 | 3.35 | 0.21 | 258 | 10611 | 1.58 | 0.09 | 288 | 11102 |
| Germany | 2010 | 3.16 | 0.09 | 1239 | 12512 | 1.54 | 0.08 | 343 | 12913 |
| Germany | 2011 | 2.83 | 0.25 | 124 | 12291 | 1.5 | 0.11 | 192 | 12664 |
| Germany | 2012 | 2.92 | 0.25 | 140 | 13912 | 1.41 | 0.08 | 312 | 13051 |
| Germany | 2013 | 2.7 | 0.24 | 130 | 12199 | 1.38 | 0.07 | 437 | 11824 |
| Germany | 2014 | 3.22 | 0.29 | 124 | 12193 | 1.51 | 0.13 | 144 | 11176 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| | | Labor income | | | | Capital income | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | Year | $\widehat{\alpha}$ | s.e. | $k$ | $N$ | $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
| Germany | 2015 | 2.54 | 0.24 | 114 | 11000 | 1.49 | 0.14 | 110 | 10625 |
| Georgia | 2010 | 2.62 | 0.15 | 305 | 4867 | 1.5 | 0.75 | 4 | 170 |
| Georgia | 2013 | 2.61 | 0.18 | 217 | 2512 | 2.68 | 1.2 | 5 | 79 |
| Georgia | 2016 | 2.88 | 0.22 | 178 | 2390 | 1.24 | 0.44 | 8 | 81 |
| Greece | 1995 | 3.13 | 0.27 | 138 | 3375 | 3.04 | 0.51 | 36 | 1033 |
| Greece | 2000 | 3.46 | 0.29 | 146 | 2580 | 2.12 | 0.29 | 55 | 724 |
| Greece | 2004 | 3.47 | 0.54 | 41 | 3987 | 1.99 | 0.34 | 34 | 1006 |
| Greece | 2007 | 2.65 | 0.31 | 75 | 4533 | 2.68 | 0.65 | 17 | 1253 |
| Greece | 2010 | 2.74 | 0.24 | 128 | 3858 | 2.54 | 0.57 | 20 | 1170 |
| Greece | 2013 | 2.75 | 0.14 | 383 | 5015 | 3.08 | 0.6 | 26 | 1517 |
| Guatemala | 2006 | 1.89 | 0.14 | 173 | 13448 | 1.74 | 0.31 | 32 | 668 |
| Guatemala | 2011 | 1.66 | 0.15 | 127 | 12622 | 1.98 | 0.31 | 41 | 438 |
| Guatemala | 2014 | 1.84 | 0.17 | 113 | 11203 | 1.9 | 0.35 | 29 | 392 |
| Hungary | 1991 | 3.1 | 0.69 | 20 | 1693 | 1.03 | 0.46 | 5 | 56 |
| Hungary | 1994 | 2.52 | 0.21 | 144 | 1532 | 2.18 | 1.54 | 2 | 85 |
| Hungary | 1999 | 3.48 | 0.48 | 53 | 1531 | 1.68 | 0.25 | 46 | 666 |
| Hungary | 2005 | 2.72 | 0.23 | 138 | 1384 | 1.63 | 0.54 | 9 | 94 |
| Hungary | 2007 | 2.87 | 0.25 | 133 | 1328 | 4.02 | 2.84 | 2 | 68 |
| Hungary | 2009 | 3.61 | 0.44 | 66 | 1250 | 2.61 | 1.31 | 4 | 41 |
| Hungary | 2012 | 2.73 | 0.4 | 46 | 1343 | 2.29 | 1.32 | 3 | 49 |
| Hungary | 2015 | 3.29 | 0.26 | 156 | 1809 | 1.25 | 0.47 | 7 | 125 |
| Iceland | 2004 | 4.49 | 0.52 | 75 | 2632 | 1.31 | 0.21 | 39 | 1836 |
| Iceland | 2007 | 3.73 | 0.25 | 216 | 2583 | 1.44 | 0.21 | 46 | 2112 |
| Iceland | 2010 | 4.15 | 0.54 | 59 | 2675 | 1.27 | 0.08 | 241 | 2994 |
| India | 2004 | 2.18 | 0.04 | 3783 | 39832 | 1.94 | 0.14 | 184 | 1874 |
| India | 2011 | 2.16 | 0.05 | 1818 | 39958 | 1.36 | 0.13 | 104 | 2011 |
| Ireland | 1987 | 2.53 | 0.46 | 30 | 2482 | 1.61 | 0.18 | 76 | 1998 |
| Ireland | 1994 | 2.17 | 0.34 | 40 | 2426 | 1.13 | 0.11 | 105 | 1113 |
| Ireland | 1995 | 1.96 | 0.42 | 22 | 2146 | 1.58 | 0.28 | 32 | 1025 |
| Ireland | 1996 | 1.76 | 0.38 | 22 | 2021 | 1.15 | 0.12 | 91 | 1022 |
| Ireland | 2000 | 3.19 | 0.34 | 90 | 1893 | 2.46 | 0.43 | 33 | 1017 |
| Ireland | 2004 | 2.22 | 0.34 | 43 | 3728 | 1.56 | 0.28 | 31 | 857 |
| Ireland | 2007 | 2.24 | 0.39 | 33 | 3137 | 1.34 | 0.21 | 40 | 1510 |
| Ireland | 2010 | 3.11 | 0.2 | 250 | 2511 | 2.46 | 0.78 | 10 | 766 |
| Israel | 1979 | 3.41 | 0.53 | 42 | 1941 | 1.24 | 0.27 | 21 | 365 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| Country | Year | Labor income $\widehat{\alpha}$ | s.e. | $k$ | $N$ | Capital income $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|
| Israel | 1986 | 3.09 | 0.16 | 353 | 3942 | 1.5 | 0.39 | 15 | 420 |
| Israel | 1992 | 3.38 | 0.18 | 349 | 4057 | 2.61 | 1.07 | 6 | 449 |
| Israel | 1997 | 2.83 | 0.16 | 324 | 4072 | 1.44 | 0.21 | 48 | 485 |
| Israel | 2001 | 2.33 | 0.35 | 45 | 4382 | 0.93 | 0.21 | 19 | 556 |
| Israel | 2005 | 3.14 | 0.15 | 452 | 4789 | 1.26 | 0.15 | 71 | 1475 |
| Israel | 2007 | 4.34 | 0.61 | 50 | 4682 | 1.47 | 0.24 | 39 | 970 |
| Israel | 2010 | 2.28 | 0.33 | 48 | 4746 | 1.07 | 0.32 | 11 | 980 |
| Israel | 2012 | 3.13 | 0.12 | 678 | 6854 | 1.41 | 0.25 | 33 | 1305 |
| Israel | 2014 | 4.61 | 0.55 | 71 | 6607 | 1.6 | 0.19 | 71 | 1330 |
| Israel | 2016 | 4.23 | 0.5 | 71 | 6968 | 2.11 | 0.2 | 112 | 1215 |
| Italy | 1986 | 2.59 | 0.33 | 62 | 6016 | 1.93 | 0.19 | 99 | 3474 |
| Italy | 1987 | 3.64 | 0.26 | 198 | 6045 | 2.52 | 0.3 | 69 | 6844 |
| Italy | 1989 | 3.55 | 0.38 | 85 | 6154 | 1.77 | 0.18 | 102 | 5865 |
| Italy | 1991 | 3.39 | 0.44 | 59 | 5827 | 2.01 | 0.24 | 69 | 6587 |
| Italy | 1993 | 3.46 | 0.16 | 464 | 5444 | 1.86 | 0.16 | 132 | 6724 |
| Italy | 1995 | 2.8 | 0.3 | 88 | 5487 | 2.27 | 0.26 | 75 | 6811 |
| Italy | 1998 | 2.71 | 0.36 | 57 | 4876 | 1.92 | 0.24 | 63 | 6191 |
| Italy | 2000 | 2.83 | 0.2 | 203 | 5279 | 1.98 | 0.24 | 66 | 6516 |
| Italy | 2004 | 2.07 | 0.17 | 146 | 4913 | 1.98 | 0.21 | 87 | 6641 |
| Italy | 2008 | 3.13 | 0.2 | 248 | 4778 | 1.81 | 0.22 | 70 | 6552 |
| Italy | 2010 | 3.1 | 0.16 | 374 | 4719 | 1.59 | 0.14 | 124 | 6490 |
| Italy | 2014 | 3.08 | 0.25 | 157 | 4401 | 1.75 | 0.13 | 182 | 6748 |
| Côte d'Ivoire | 2002 | 2.02 | 0.19 | 115 | 9811 | 1.66 | 0.31 | 29 | 618 |
| Côte d'Ivoire | 2008 | 1.74 | 0.07 | 584 | 11594 | 0.64 | 0.23 | 8 | 621 |
| Côte d'Ivoire | 2015 | 1.77 | 0.05 | 1127 | 11293 | 1.12 | 0.26 | 19 | 664 |
| Japan | 2008 | 3.25 | 0.2 | 270 | 3256 | 2.02 | 0.49 | 17 | 598 |
| Lithuania | 2010 | 4.74 | 0.36 | 169 | 3640 | 1.4 | 0.27 | 28 | 564 |
| Lithuania | 2013 | 4.64 | 0.71 | 43 | 3785 | 2.25 | 0.85 | 7 | 523 |
| Luxembourg | 1985 | 5.07 | 0.46 | 120 | 1552 | 2.02 | 0.46 | 19 | 199 |
| Luxembourg | 1991 | 4.78 | 0.48 | 101 | 1535 | 1.45 | 0.21 | 49 | 716 |
| Luxembourg | 1994 | 4.37 | 0.5 | 76 | 1362 | 3.11 | 0.6 | 27 | 531 |
| Luxembourg | 1997 | 4.57 | 0.35 | 169 | 1906 | 1.91 | 0.58 | 11 | 779 |
| Luxembourg | 2000 | 3.84 | 0.66 | 34 | 1840 | 1.85 | 0.41 | 20 | 892 |
| Luxembourg | 2004 | 3.44 | 0.21 | 271 | 2753 | 2.99 | 0.43 | 49 | 887 |
| Luxembourg | 2007 | 2.78 | 0.16 | 302 | 3028 | 2.49 | 0.41 | 37 | 2066 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| | | Labor income | | | | Capital income | | | |
|---|---|---|---|---|---|---|---|---|---|
| Country | Year | $\widehat{\alpha}$ | s.e. | $k$ | $N$ | $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
| Luxembourg | 2010 | 3.18 | 0.28 | 129 | 4111 | 2.68 | 0.45 | 36 | 3494 |
| Luxembourg | 2013 | 3.2 | 0.49 | 43 | 2828 | 1.42 | 0.1 | 215 | 2534 |
| Mexico | 1984 | 2.27 | 0.31 | 54 | 4461 | 1.99 | 0.45 | 20 | 297 |
| Mexico | 1989 | 2.14 | 0.08 | 709 | 10876 | 1.17 | 0.15 | 60 | 602 |
| Mexico | 1992 | 1.95 | 0.06 | 986 | 9959 | 1.86 | 0.33 | 31 | 414 |
| Mexico | 1994 | 2.04 | 0.06 | 1139 | 12068 | 2.87 | 1.17 | 6 | 450 |
| Mexico | 1996 | 2.02 | 0.06 | 1311 | 13128 | 1.42 | 0.22 | 40 | 505 |
| Mexico | 1998 | 2.05 | 0.07 | 834 | 10092 | 2.42 | 0.86 | 8 | 393 |
| Mexico | 2000 | 2.51 | 0.23 | 115 | 9262 | 1.73 | 0.45 | 15 | 348 |
| Mexico | 2002 | 3.24 | 0.21 | 239 | 15905 | 3.2 | 1.01 | 10 | 587 |
| Mexico | 2004 | 2.15 | 0.05 | 1989 | 20928 | 0.95 | 0.27 | 12 | 1055 |
| Mexico | 2008 | 2.08 | 0.04 | 2622 | 26414 | 1.61 | 0.23 | 49 | 1635 |
| Mexico | 2010 | 2.64 | 0.12 | 471 | 24218 | 1.75 | 0.39 | 20 | 1323 |
| Mexico | 2012 | 2.54 | 0.17 | 219 | 8032 | 2.81 | 0.64 | 19 | 433 |
| Netherlands | 1983 | 4.51 | 0.8 | 32 | 3090 | 2.97 | 0.9 | 11 | 182 |
| Netherlands | 1987 | 3.92 | 0.73 | 29 | 2792 | 2.12 | 0.5 | 18 | 231 |
| Netherlands | 1990 | 3.13 | 0.54 | 34 | 2971 | 1.78 | 0.33 | 30 | 2570 |
| Netherlands | 1993 | 3.62 | 0.56 | 42 | 3565 | 1.5 | 0.16 | 92 | 2423 |
| Netherlands | 1999 | 3.41 | 0.6 | 32 | 3061 | 2.02 | 0.45 | 20 | 1942 |
| Netherlands | 2004 | 3.17 | 0.29 | 116 | 7166 | 1.58 | 0.13 | 142 | 8171 |
| Netherlands | 2007 | 2.98 | 0.26 | 135 | 8011 | 1.01 | 0.04 | 544 | 9136 |
| Netherlands | 2010 | 3.27 | 0.27 | 145 | 8001 | 1.4 | 0.07 | 395 | 9539 |
| Netherlands | 2013 | 3.1 | 0.31 | 101 | 7808 | 1.33 | 0.06 | 547 | 9486 |
| Norway | 1979 | 1.5 | 0.05 | 781 | 8276 | 2.06 | 0.17 | 141 | 6048 |
| Norway | 1986 | 4.75 | 0.23 | 418 | 4254 | 2.31 | 0.31 | 57 | 2588 |
| Norway | 1991 | 3.8 | 0.2 | 359 | 7361 | 1.8 | 0.1 | 346 | 7448 |
| Norway | 1995 | 3.17 | 0.28 | 131 | 8027 | 1.18 | 0.11 | 124 | 9800 |
| Norway | 2000 | 2.74 | 0.25 | 116 | 11474 | 1.08 | 0.08 | 161 | 12804 |
| Norway | 2004 | 3.3 | 0.28 | 141 | 10947 | 0.93 | 0.06 | 251 | 12979 |
| Norway | 2007 | 3.1 | 0.08 | 1701 | 169708 | 1.37 | 0.03 | 2156 | 215363 |
| Norway | 2010 | 3.36 | 0.05 | 4809 | 177229 | 0.89 | 0.01 | 16510 | 225584 |
| Norway | 2013 | 2.99 | 0.05 | 3693 | 183146 | 0.89 | 0.01 | 22423 | 233192 |
| Panama | 2007 | 2.73 | 0.23 | 146 | 11693 | 1.21 | 0.16 | 56 | 566 |
| Panama | 2010 | 2.23 | 0.09 | 619 | 11855 | 2.66 | 1 | 7 | 525 |
| Panama | 2013 | 2.95 | 0.24 | 145 | 10577 | 2.16 | 0.46 | 22 | 337 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| Country | Year | Labor income $\widehat{\alpha}$ | s.e. | $k$ | $N$ | Capital income $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|
| Paraguay | 2000 | 1.68 | 0.06 | 689 | 7685 | 1.5 | 0.21 | 51 | 585 |
| Paraguay | 2004 | 1.83 | 0.07 | 709 | 7434 | 1.68 | 0.34 | 25 | 343 |
| Paraguay | 2007 | 1.6 | 0.15 | 119 | 4528 | 1.52 | 0.3 | 26 | 263 |
| Paraguay | 2010 | 1.54 | 0.2 | 62 | 4697 | 1.69 | 0.47 | 13 | 261 |
| Paraguay | 2013 | 2.1 | 0.17 | 152 | 5073 | 1.55 | 0.47 | 11 | 318 |
| Paraguay | 2016 | 2.02 | 0.12 | 298 | 9470 | 1.56 | 0.24 | 43 | 468 |
| Peru | 2004 | 2.51 | 0.16 | 256 | 17289 | 1.66 | 0.12 | 177 | 2193 |
| Peru | 2007 | 3 | 0.19 | 250 | 20464 | 1.48 | 0.1 | 242 | 2571 |
| Peru | 2010 | 2.62 | 0.19 | 199 | 19720 | 1.88 | 0.24 | 61 | 3137 |
| Peru | 2013 | 3.3 | 0.2 | 282 | 27670 | 2.12 | 0.24 | 80 | 3827 |
| Poland | 1986 | 3.57 | 0.26 | 186 | 9213 | NaN | NaN | NaN | NaN |
| Poland | 1992 | 3.57 | 0.34 | 111 | 5944 | 1.14 | 0.2 | 34 | 456 |
| Poland | 1995 | 2.26 | 0.15 | 226 | 21091 | 1.63 | 0.34 | 23 | 230 |
| Poland | 1999 | 3.09 | 0.06 | 2418 | 24216 | 2.62 | 0.5 | 27 | 284 |
| Poland | 2004 | 2.72 | 0.06 | 2216 | 23557 | 1.36 | 0.28 | 24 | 305 |
| Poland | 2007 | 2.65 | 0.16 | 287 | 27872 | 1.39 | 0.24 | 33 | 340 |
| Poland | 2010 | 2.86 | 0.05 | 2761 | 27640 | 1.72 | 0.38 | 21 | 366 |
| Poland | 2013 | 2.75 | 0.05 | 2643 | 26475 | 1.49 | 0.26 | 33 | 422 |
| Poland | 2016 | 2.93 | 0.07 | 1905 | 25983 | 2.39 | 0.47 | 26 | 383 |
| Romania | 1995 | 2.95 | 0.15 | 372 | 31519 | 1.5 | 0.33 | 21 | 325 |
| Romania | 1997 | 3.05 | 0.17 | 322 | 32122 | 1.74 | 0.29 | 36 | 374 |
| Russia | 2000 | 2.11 | 0.13 | 253 | 2631 | 0.86 | 0.5 | 3 | 55 |
| Russia | 2004 | 3.88 | 0.43 | 83 | 2705 | 1.5 | 1.06 | 2 | 66 |
| Russia | 2007 | 4.03 | 0.61 | 44 | 2986 | 2.07 | 1.19 | 3 | 81 |
| Russia | 2010 | 3.41 | 0.23 | 218 | 5025 | 3.18 | 1.06 | 9 | 107 |
| Russia | 2011 | 4.19 | 0.3 | 191 | 8697 | 2.68 | 0.63 | 18 | 513 |
| Russia | 2013 | 3.93 | 0.15 | 726 | 38297 | 2.87 | 0.37 | 61 | 4360 |
| Russia | 2014 | 4.32 | 0.16 | 735 | 38433 | 2.15 | 0.17 | 153 | 4412 |
| Russia | 2015 | 4.31 | 0.12 | 1272 | 50779 | 1.73 | 0.1 | 301 | 5752 |
| Russia | 2016 | 4.73 | 0.12 | 1554 | 134781 | 3.44 | 0.17 | 400 | 15716 |
| Serbia | 2006 | 3.53 | 0.33 | 113 | 3491 | 2.46 | 1.74 | 2 | 108 |
| Serbia | 2010 | 2.76 | 0.45 | 38 | 3270 | 2.19 | 0.77 | 8 | 107 |
| Serbia | 2013 | 1.96 | 0.34 | 33 | 3201 | 2.13 | 0.71 | 9 | 86 |
| Serbia | 2016 | 3.24 | 0.2 | 276 | 4566 | 3.37 | 0.87 | 15 | 146 |
| Slovakia | 1992 | 3.28 | 0.31 | 115 | 11439 | 1.31 | 0.31 | 18 | 177 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| Country | Year | Labor income $\widehat{\alpha}$ | s.e. | $k$ | $N$ | Capital income $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|
| Slovakia | 1996 | 4.09 | 0.11 | 1318 | 13176 | 1.44 | 0.22 | 44 | 709 |
| Slovakia | 2004 | 2.59 | 0.28 | 86 | 3987 | 1.64 | 0.47 | 12 | 319 |
| Slovakia | 2007 | 3.89 | 0.53 | 54 | 4538 | 2.46 | 0.68 | 13 | 653 |
| Slovakia | 2010 | 3.49 | 0.18 | 393 | 4372 | 1.71 | 0.36 | 23 | 1024 |
| Slovakia | 2013 | 2.47 | 0.36 | 48 | 4527 | 2.17 | 0.53 | 17 | 1289 |
| Slovenia | 1997 | 4.84 | 0.37 | 174 | 2378 | 1.6 | 0.31 | 27 | 376 |
| Slovenia | 1999 | 4.34 | 0.23 | 342 | 3492 | 1.47 | 0.26 | 32 | 601 |
| Slovenia | 2004 | 4.47 | 0.25 | 326 | 3275 | 2.17 | 0.4 | 29 | 521 |
| Slovenia | 2007 | 4.47 | 0.27 | 267 | 3219 | 1.58 | 0.23 | 48 | 501 |
| Slovenia | 2010 | 4.68 | 0.26 | 323 | 3468 | 2.27 | 0.8 | 8 | 493 |
| Slovenia | 2012 | 4.57 | 0.28 | 263 | 3252 | 1.36 | 0.11 | 150 | 1841 |
| South Africa | 2008 | 2.42 | 0.33 | 54 | 4866 | 2.15 | 0.62 | 12 | 198 |
| South Africa | 2010 | 2.55 | 0.26 | 98 | 3859 | 3.36 | 2.38 | 2 | 93 |
| South Africa | 2012 | 2.02 | 0.11 | 328 | 5112 | 1.09 | 0.45 | 6 | 154 |
| Rep. of Korea | 2006 | 3.71 | 0.1 | 1438 | 14390 | 2.37 | 0.32 | 55 | 4353 |
| Rep. of Korea | 2008 | 3.62 | 0.1 | 1196 | 12542 | 2.23 | 0.34 | 42 | 3616 |
| Rep. of Korea | 2010 | 3.65 | 0.11 | 1196 | 12276 | 1.94 | 0.27 | 50 | 3003 |
| Rep. of Korea | 2012 | 3.74 | 0.11 | 1112 | 11911 | 1.66 | 0.15 | 119 | 3329 |
| Spain | 1980 | 3.57 | 0.08 | 1859 | 19651 | 1.64 | 0.15 | 123 | 1470 |
| Spain | 1985 | 3.37 | 0.23 | 216 | 2707 | 1.7 | 0.37 | 21 | 344 |
| Spain | 1990 | 3.76 | 0.09 | 1591 | 16178 | 2.05 | 0.23 | 77 | 4036 |
| Spain | 1995 | 3.34 | 0.33 | 101 | 4088 | 1.62 | 0.12 | 171 | 2249 |
| Spain | 2000 | 3.15 | 0.2 | 245 | 3379 | 1.6 | 0.2 | 63 | 4206 |
| Spain | 2004 | 3.78 | 0.13 | 803 | 9175 | 1.74 | 0.23 | 58 | 4433 |
| Spain | 2007 | 4.74 | 0.43 | 119 | 9701 | 2.08 | 0.26 | 64 | 5327 |
| Spain | 2010 | 6.08 | 0.49 | 152 | 8822 | 2.93 | 0.5 | 35 | 3043 |
| Spain | 2013 | 4.22 | 0.33 | 165 | 8823 | 2.32 | 0.28 | 68 | 6681 |
| Spain | 2016 | 3.61 | 0.24 | 223 | 10165 | 2 | 0.2 | 102 | 7451 |
| Sweden | 1967 | 3.45 | 0.35 | 95 | 4912 | 1.51 | 0.15 | 99 | 988 |
| Sweden | 1975 | 3.77 | 0.14 | 709 | 9535 | 1.67 | 0.18 | 82 | 7845 |
| Sweden | 1981 | 4.15 | 0.15 | 726 | 8635 | 2.08 | 0.09 | 582 | 6092 |
| Sweden | 1987 | 4.39 | 0.16 | 752 | 8658 | 1.45 | 0.16 | 81 | 7953 |
| Sweden | 1992 | 4.25 | 0.16 | 694 | 10824 | 1.79 | 0.05 | 1072 | 11215 |
| Sweden | 1995 | 3.78 | 0.11 | 1130 | 11655 | 1.53 | 0.05 | 959 | 12993 |
| Sweden | 2000 | 2.79 | 0.27 | 108 | 10319 | 1.08 | 0.03 | 1041 | 11273 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| Country | Year | Labor income $\widehat{\alpha}$ | s.e. | $k$ | $N$ | Capital income $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|
| Sweden | 2005 | 2.26 | 0.2 | 127 | 11951 | 1.02 | 0.03 | 1161 | 12120 |
| Switzerland | 1982 | 2 | 0.16 | 165 | 5570 | 1.27 | 0.07 | 330 | 4233 |
| Switzerland | 1992 | 3.21 | 0.31 | 110 | 4486 | 1.45 | 0.11 | 179 | 4846 |
| Switzerland | 2002 | 2.72 | 0.38 | 50 | 3140 | 1.24 | 0.08 | 245 | 2646 |
| Switzerland | 2000 | 2.64 | 0.47 | 32 | 3074 | 1.7 | 0.2 | 75 | 2578 |
| Switzerland | 2004 | 3.99 | 0.5 | 65 | 2697 | 1.3 | 0.09 | 203 | 2648 |
| Switzerland | 2007 | 2.22 | 0.23 | 93 | 5424 | 2.49 | 0.31 | 63 | 5057 |
| Switzerland | 2010 | 2.42 | 0.31 | 59 | 5759 | 1.83 | 0.22 | 71 | 6749 |
| Switzerland | 2013 | 3.6 | 0.3 | 140 | 5097 | 2.39 | 0.29 | 69 | 6190 |
| Taiwan | 1981 | 3.86 | 0.31 | 160 | 14997 | 1.89 | 0.18 | 107 | 10635 |
| Taiwan | 1986 | 3.23 | 0.26 | 160 | 15911 | 1.98 | 0.15 | 165 | 12864 |
| Taiwan | 1991 | 3.84 | 0.1 | 1546 | 15756 | 1.5 | 0.06 | 577 | 14978 |
| Taiwan | 1995 | 4.07 | 0.11 | 1302 | 13619 | 1.86 | 0.09 | 431 | 14184 |
| Taiwan | 1997 | 4.39 | 0.22 | 385 | 12572 | 2.11 | 0.14 | 222 | 13311 |
| Taiwan | 2000 | 3.74 | 0.11 | 1213 | 12301 | 2.49 | 0.21 | 135 | 13396 |
| Taiwan | 2005 | 4.08 | 0.16 | 689 | 11903 | 2.1 | 0.13 | 246 | 13127 |
| Taiwan | 2007 | 3.93 | 0.28 | 192 | 12042 | 2.26 | 0.19 | 137 | 13290 |
| Taiwan | 2010 | 3.74 | 0.13 | 840 | 12748 | 2.17 | 0.17 | 159 | 14287 |
| Taiwan | 2013 | 3.68 | 0.13 | 841 | 13300 | 1.65 | 0.07 | 510 | 15615 |
| Taiwan | 2016 | 3.59 | 0.1 | 1353 | 13648 | 1.95 | 0.12 | 250 | 16449 |
| United Kingdom | 1969 | 3.47 | 0.45 | 59 | 5669 | 1.33 | 0.14 | 90 | 4102 |
| United Kingdom | 1974 | 3.05 | 0.42 | 53 | 5181 | 1.84 | 0.25 | 53 | 3547 |
| United Kingdom | 1979 | 4.39 | 0.2 | 485 | 4937 | 1.82 | 0.2 | 82 | 4280 |
| United Kingdom | 1986 | 4.02 | 0.19 | 438 | 4515 | 1.96 | 0.2 | 96 | 4942 |
| United Kingdom | 1991 | 2.76 | 0.34 | 66 | 4445 | 1.37 | 0.06 | 480 | 5174 |
| United Kingdom | 1994 | 2.51 | 0.18 | 203 | 15751 | 1.86 | 0.12 | 232 | 18563 |
| United Kingdom | 1995 | 3 | 0.38 | 63 | 4091 | 1.87 | 0.27 | 47 | 4584 |
| United Kingdom | 1999 | 2.44 | 0.15 | 250 | 15200 | 1.93 | 0.15 | 173 | 17223 |
| United Kingdom | 2004 | 2.23 | 0.17 | 171 | 17026 | 1.68 | 0.12 | 190 | 18531 |
| United Kingdom | 2007 | 3.01 | 0.22 | 180 | 15272 | 2.01 | 0.15 | 173 | 16371 |
| United Kingdom | 2010 | 2.98 | 0.24 | 156 | 15237 | 1.71 | 0.16 | 121 | 9839 |
| United Kingdom | 2013 | 3.2 | 0.25 | 170 | 12258 | 2.18 | 0.25 | 78 | 7714 |
| United Kingdom | 2016 | 2.66 | 0.22 | 145 | 11768 | 1.5 | 0.11 | 177 | 7340 |
| United States | 1974 | 3.92 | 0.17 | 514 | 9366 | 1.89 | 0.25 | 59 | 5558 |
| United States | 1979 | 4.18 | 0.18 | 564 | 52783 | 1.93 | 0.08 | 527 | 44749 |

Table 2: Point estimates of income Pareto exponents across countries and years.

| Country | Year | Labor income $\widehat{\alpha}$ | s.e. | $k$ | $N$ | Capital income $\widehat{\alpha}$ | s.e. | $k$ | $N$ |
|---|---|---|---|---|---|---|---|---|---|
| United States | 1986 | 3.5 | 0.07 | 2304 | 45660 | 2.02 | 0.1 | 401 | 38274 |
| United States | 1991 | 3.57 | 0.17 | 466 | 46199 | 2.16 | 0.1 | 433 | 38875 |
| United States | 1994 | 2.63 | 0.04 | 3614 | 44261 | 2.1 | 0.11 | 387 | 37355 |
| United States | 1997 | 2.62 | 0.04 | 3805 | 39812 | 2.32 | 0.13 | 313 | 30913 |
| United States | 2000 | 2.59 | 0.03 | 6343 | 64575 | 2.43 | 0.11 | 482 | 46961 |
| United States | 2004 | 2.65 | 0.04 | 3590 | 62334 | 2.45 | 0.12 | 434 | 42354 |
| United States | 2007 | 2.79 | 0.04 | 4879 | 62005 | 3.52 | 0.17 | 439 | 39315 |
| United States | 2010 | 2.78 | 0.04 | 5213 | 59937 | 3.03 | 0.16 | 378 | 37388 |
| United States | 2013 | 2.58 | 0.05 | 3060 | 40721 | 3.46 | 0.19 | 333 | 24494 |
| United States | 2016 | 2.44 | 0.04 | 3657 | 54727 | 4.14 | 0.17 | 565 | 45401 |
| Uruguay | 2004 | 2.46 | 0.11 | 467 | 13671 | 2.01 | 0.3 | 46 | 1241 |
| Uruguay | 2007 | 2.89 | 0.12 | 591 | 37097 | 1.45 | 0.07 | 402 | 4236 |
| Uruguay | 2010 | 2.93 | 0.1 | 778 | 35428 | 1.87 | 0.23 | 65 | 4085 |
| Uruguay | 2013 | 2.69 | 0.05 | 3498 | 35264 | 2.74 | 0.44 | 38 | 3497 |
| Uruguay | 2016 | 3.13 | 0.16 | 402 | 33484 | 1.5 | 0.09 | 313 | 3632 |
| Vietnam | 2011 | 2.8 | 0.28 | 101 | 9282 | 1.13 | 0.25 | 20 | 1362 |
| Vietnam | 2013 | 2.8 | 0.11 | 706 | 9282 | 1.66 | 0.17 | 98 | 1384 |

Note: $\widehat{\alpha}$: *point estimate of Pareto exponent; s.e.: standard error (calculated using the inverse Fisher information); $k$: the number of order statistics used for the Hill-estimator; $N$: the number of positive labor (resp. capital) income observations.*

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| Australia | 1981 | 5.26 | 0.24 | 2.1 | 0.1 | 9488 | Yes |
| Australia | 1985 | 4.22 | 0.26 | 1.4 | 0.09 | 5232 | Yes |
| Australia | 1989 | 3.95 | 0.17 | 1.46 | 0.06 | 10629 | Yes |
| Australia | 1995 | 2.91 | 0.22 | 1.7 | 0.13 | 3364 | Yes |
| Australia | 2001 | 3.24 | 0.26 | 1.45 | 0.12 | 3105 | Yes |
| Australia | 2003 | 3.25 | 0.22 | 1.51 | 0.1 | 4473 | Yes |
| Australia | 2004 | 3.38 | 0.19 | 1.41 | 0.08 | 6145 | Yes |
| Australia | 2008 | 3.3 | 0.21 | 1.27 | 0.08 | 4749 | Yes |
| Australia | 2010 | 3.31 | 0.16 | 1.29 | 0.06 | 9093 | Yes |
| Australia | 2014 | 3.14 | 0.14 | 1.19 | 0.05 | 9616 | Yes |
| Austria | 1994 | 3.12 | 0.34 | 1.59 | 0.17 | 1695 | Yes |

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| Austria | 1997 | 3.55 | 0.37 | 1.78 | 0.19 | 1800 | No |
| Austria | 2000 | 3.1 | 0.35 | 2.1 | 0.24 | 1584 | No |
| Austria | 2004 | 3.34 | 0.24 | 0.99 | 0.07 | 3750 | Yes |
| Austria | 2007 | 3.23 | 0.23 | 1.17 | 0.08 | 4101 | Yes |
| Austria | 2010 | 3.51 | 0.24 | 1.05 | 0.07 | 4323 | Yes |
| Austria | 2013 | 3.36 | 0.24 | 1.12 | 0.08 | 4022 | Yes |
| Belgium | 1997 | 4.25 | 0.35 | 1.82 | 0.15 | 2906 | Yes |
| Brazil | 2006 | 3.32 | 0.21 | 1.53 | 0.1 | 4804 | No |
| Brazil | 2009 | 3.19 | 0.21 | 1.98 | 0.13 | 4724 | No |
| Brazil | 2011 | 2.89 | 0.24 | 1.7 | 0.14 | 2897 | No |
| Brazil | 2013 | 2.94 | 0.25 | 1.48 | 0.12 | 2869 | Yes |
| Canada | 1971 | 3.56 | 0.16 | 1.66 | 0.07 | 9970 | Yes |
| Canada | 1975 | 4.02 | 0.17 | 1.84 | 0.08 | 10717 | Yes |
| Canada | 1981 | 4.59 | 0.22 | 2.01 | 0.1 | 8342 | Yes |
| Canada | 1987 | 4.78 | 0.3 | 1.88 | 0.12 | 5190 | Yes |
| Canada | 1991 | 4.34 | 0.2 | 2 | 0.09 | 9847 | Yes |
| Canada | 1994 | 4.07 | 0.15 | 1.75 | 0.07 | 14077 | Yes |
| Canada | 1997 | 4.01 | 0.17 | 1.79 | 0.08 | 11273 | Yes |
| Canada | 1998 | 3.22 | 0.12 | 1.46 | 0.06 | 13486 | Yes |
| Canada | 2000 | 3.17 | 0.12 | 1.47 | 0.06 | 13264 | Yes |
| Canada | 2004 | 3.15 | 0.13 | 1.56 | 0.06 | 11861 | Yes |
| Canada | 2007 | 2.85 | 0.11 | 1.49 | 0.06 | 12533 | Yes |
| Canada | 2010 | 3.06 | 0.13 | 1.4 | 0.06 | 10341 | Yes |
| Canada | 2013 | 3.93 | 0.18 | 1.56 | 0.07 | 9741 | Yes |
| Chile | 1990 | 2.24 | 0.28 | 1.62 | 0.21 | 1242 | No |
| Chile | 1992 | 3.42 | 0.37 | 1.76 | 0.19 | 1678 | Yes |
| Chile | 1994 | 2.61 | 0.26 | 1.91 | 0.19 | 2071 | No |
| Chile | 1996 | 2.71 | 0.21 | 1.52 | 0.12 | 3437 | Yes |
| Chile | 1998 | 2.43 | 0.19 | 1.64 | 0.13 | 3335 | No |
| Chile | 2000 | 2.28 | 0.15 | 1.38 | 0.09 | 4432 | Yes |
| Chile | 2003 | 2.28 | 0.15 | 1.45 | 0.1 | 4637 | No |
| Chile | 2006 | 2.31 | 0.14 | 1.38 | 0.08 | 5374 | Yes |
| Chile | 2009 | 3.02 | 0.22 | 1.48 | 0.11 | 3619 | Yes |
| Chile | 2011 | 3.48 | 0.27 | 1.82 | 0.14 | 3312 | Yes |
| Chile | 2013 | 2.87 | 0.21 | 1.76 | 0.13 | 3635 | No |
| Chile | 2015 | 3.27 | 0.2 | 1.71 | 0.11 | 5314 | Yes |
| China | 2002 | 4.24 | 0.41 | 1.72 | 0.17 | 2167 | Yes |

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| China | 2013 | 3.1 | 0.14 | 2.06 | 0.09 | 10098 | No |
| Colombia | 2004 | 2.37 | 0.28 | 1.97 | 0.23 | 1411 | No |
| Colombia | 2007 | 2.02 | 0.06 | 1.7 | 0.05 | 23816 | Yes |
| Colombia | 2010 | 2.51 | 0.07 | 1.63 | 0.05 | 24975 | No |
| Colombia | 2013 | 2.55 | 0.07 | 1.74 | 0.05 | 25674 | Yes |
| Czech Rep | 1996 | 3 | 0.24 | 1.14 | 0.09 | 3077 | Yes |
| Czech Rep | 2007 | 3.62 | 0.39 | 1.11 | 0.12 | 1735 | Yes |
| Czech Rep | 2010 | 4.09 | 0.49 | 1.23 | 0.15 | 1422 | Yes |
| Czech Rep | 2013 | 3.12 | 0.4 | 1.54 | 0.2 | 1198 | No |
| Denmark | 1987 | 4.46 | 0.21 | 1.64 | 0.08 | 9199 | Yes |
| Denmark | 1992 | 4.57 | 0.21 | 1.46 | 0.07 | 9164 | Yes |
| Denmark | 1995 | 4.68 | 0.09 | 1.26 | 0.02 | 57306 | Yes |
| Denmark | 2000 | 4.26 | 0.08 | 1.19 | 0.02 | 59549 | Yes |
| Denmark | 2004 | 4.03 | 0.07 | 1.17 | 0.02 | 59824 | Yes |
| Denmark | 2007 | 3.82 | 0.07 | 1.17 | 0.02 | 61255 | Yes |
| Denmark | 2010 | 3.37 | 0.06 | 1.2 | 0.02 | 59488 | Yes |
| Denmark | 2013 | 3.47 | 0.06 | 1.13 | 0.02 | 60880 | Yes |
| Estonia | 2007 | 4.53 | 0.43 | 0.67 | 0.06 | 2250 | Yes |
| Estonia | 2010 | 4.68 | 0.48 | 0.91 | 0.09 | 1948 | Yes |
| Estonia | 2013 | 3.65 | 0.42 | 1.16 | 0.13 | 1549 | Yes |
| Finland | 1987 | 4.35 | 0.22 | 1.45 | 0.07 | 7906 | Yes |
| Finland | 1991 | 4.48 | 0.22 | 1.43 | 0.07 | 8332 | Yes |
| Finland | 1995 | 4.5 | 0.31 | 1.25 | 0.09 | 4236 | Yes |
| Finland | 2000 | 3.53 | 0.21 | 1.09 | 0.06 | 5923 | Yes |
| Finland | 2004 | 3.91 | 0.19 | 1.02 | 0.05 | 8061 | Yes |
| Finland | 2007 | 3.82 | 0.19 | 1.01 | 0.05 | 8502 | Yes |
| Finland | 2010 | 3.91 | 0.2 | 1.05 | 0.05 | 7537 | Yes |
| Finland | 2013 | 3.9 | 0.19 | 1.04 | 0.05 | 8899 | Yes |
| France | 1978 | 2.4 | 0.28 | 1.75 | 0.21 | 1426 | No |
| France | 1984 | 1.52 | 0.15 | 1.73 | 0.17 | 1974 | No |
| France | 1989 | 3.43 | 0.37 | 1.65 | 0.18 | 1677 | Yes |
| France | 1994 | 3.13 | 0.16 | 1.68 | 0.08 | 7880 | Yes |
| France | 2000 | 3.51 | 0.19 | 1.72 | 0.09 | 7112 | Yes |
| France | 2005 | 3.33 | 0.17 | 1.53 | 0.08 | 7987 | Yes |
| France | 2010 | 3.02 | 0.12 | 1.49 | 0.06 | 11660 | Yes |
| Germany | 1973 | 3.56 | 0.08 | 2.13 | 0.05 | 37614 | No |
| Germany | 1978 | 3.36 | 0.08 | 2.18 | 0.05 | 35731 | No |

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| Germany | 1983 | 4.54 | 0.11 | 2.23 | 0.06 | 32288 | Yes |
| Germany | 1984 | 3.96 | 0.27 | 1.03 | 0.07 | 4240 | Yes |
| Germany | 1987 | 4.23 | 0.3 | 1.17 | 0.08 | 3863 | Yes |
| Germany | 1989 | 3.29 | 0.24 | 1.18 | 0.09 | 3733 | Yes |
| Germany | 1991 | 4.77 | 0.29 | 1.1 | 0.07 | 5448 | Yes |
| Germany | 1994 | 4.54 | 0.28 | 1.32 | 0.08 | 5384 | Yes |
| Germany | 1995 | 4.65 | 0.29 | 1.33 | 0.08 | 5275 | Yes |
| Germany | 1998 | 4.56 | 0.27 | 1.31 | 0.08 | 5531 | Yes |
| Germany | 2000 | 3.91 | 0.19 | 1.51 | 0.07 | 8784 | Yes |
| Germany | 2001 | 3.46 | 0.16 | 1.31 | 0.06 | 9273 | Yes |
| Germany | 2002 | 3.57 | 0.17 | 1.35 | 0.06 | 8850 | Yes |
| Germany | 2003 | 3.64 | 0.18 | 1.28 | 0.06 | 8600 | Yes |
| Germany | 2004 | 3.67 | 0.18 | 1.29 | 0.06 | 8300 | Yes |
| Germany | 2005 | 3.29 | 0.16 | 1.27 | 0.06 | 8869 | Yes |
| Germany | 2006 | 3.28 | 0.16 | 1.32 | 0.06 | 8276 | Yes |
| Germany | 2007 | 3.44 | 0.17 | 1.35 | 0.07 | 7778 | Yes |
| Germany | 2008 | 3.22 | 0.17 | 1.29 | 0.07 | 7295 | Yes |
| Germany | 2009 | 3.43 | 0.15 | 1.37 | 0.06 | 10611 | Yes |
| Germany | 2010 | 3.44 | 0.14 | 1.29 | 0.05 | 12512 | Yes |
| Germany | 2011 | 3.3 | 0.13 | 1.28 | 0.05 | 12291 | Yes |
| Germany | 2012 | 3.43 | 0.13 | 1.31 | 0.05 | 13051 | Yes |
| Germany | 2013 | 3.4 | 0.14 | 1.32 | 0.05 | 11824 | Yes |
| Germany | 2014 | 3.78 | 0.16 | 1.3 | 0.06 | 11176 | Yes |
| Germany | 2015 | 3.09 | 0.13 | 1.31 | 0.06 | 10625 | Yes |
| Greece | 1995 | 3.7 | 0.51 | 2.83 | 0.39 | 1033 | No |
| Greece | 2004 | 3.64 | 0.52 | 2.12 | 0.3 | 1006 | No |
| Greece | 2007 | 2.81 | 0.35 | 1.97 | 0.25 | 1253 | No |
| Greece | 2010 | 3.01 | 0.39 | 2.09 | 0.27 | 1170 | No |
| Greece | 2013 | 2.68 | 0.31 | 2.22 | 0.25 | 1517 | No |
| Iceland | 2004 | 4.71 | 0.49 | 1.15 | 0.12 | 1840 | Yes |
| Iceland | 2007 | 4.4 | 0.43 | 1.16 | 0.11 | 2113 | Yes |
| Iceland | 2010 | 4.51 | 0.39 | 1.13 | 0.1 | 2675 | Yes |
| India | 2004 | 2.85 | 0.29 | 2.47 | 0.25 | 1876 | No |
| India | 2011 | 2.21 | 0.22 | 1.43 | 0.14 | 2027 | No |
| Ireland | 1987 | 3.41 | 0.34 | 1.29 | 0.13 | 1998 | Yes |
| Ireland | 1994 | 2.54 | 0.34 | 1.26 | 0.17 | 1114 | Yes |
| Ireland | 1995 | 2.31 | 0.32 | 1.3 | 0.18 | 1026 | Yes |

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| Ireland | 1996 | 2.68 | 0.38 | 1.56 | 0.22 | 1023 | No |
| Ireland | 2000 | 3.44 | 0.41 | 1.7 | 0.2 | 1371 | Yes |
| Ireland | 2007 | 2.64 | 0.3 | 1.49 | 0.17 | 1510 | Yes |
| Israel | 2005 | 3.67 | 0.43 | 1.25 | 0.15 | 1475 | Yes |
| Israel | 2012 | 3.49 | 0.43 | 1.3 | 0.16 | 1305 | Yes |
| Israel | 2014 | 4.76 | 0.59 | 1.69 | 0.21 | 1330 | Yes |
| Israel | 2016 | 4.23 | 0.54 | 2.14 | 0.27 | 1215 | Yes |
| Italy | 1986 | 3.17 | 0.24 | 1.85 | 0.14 | 3474 | Yes |
| Italy | 1987 | 3.51 | 0.2 | 1.66 | 0.1 | 6045 | Yes |
| Italy | 1989 | 3.95 | 0.23 | 1.56 | 0.09 | 5865 | Yes |
| Italy | 1991 | 4.43 | 0.26 | 1.64 | 0.1 | 5827 | Yes |
| Italy | 1993 | 3.76 | 0.23 | 1.52 | 0.09 | 5444 | Yes |
| Italy | 1995 | 3.24 | 0.2 | 1.62 | 0.1 | 5487 | Yes |
| Italy | 1998 | 3.37 | 0.22 | 1.46 | 0.09 | 4876 | Yes |
| Italy | 2000 | 3.05 | 0.19 | 1.33 | 0.08 | 5280 | Yes |
| Italy | 2004 | 2.39 | 0.15 | 1.52 | 0.1 | 4913 | Yes |
| Italy | 2008 | 3.13 | 0.2 | 1.44 | 0.09 | 4778 | Yes |
| Italy | 2010 | 3.35 | 0.22 | 1.34 | 0.09 | 4719 | Yes |
| Italy | 2014 | 2.75 | 0.19 | 1.61 | 0.11 | 4402 | Yes |
| Luxembourg | 2007 | 3.26 | 0.32 | 1.61 | 0.16 | 2085 | Yes |
| Luxembourg | 2010 | 3.43 | 0.26 | 1.71 | 0.13 | 3494 | Yes |
| Luxembourg | 2013 | 3.68 | 0.33 | 1.59 | 0.14 | 2534 | No |
| Mexico | 2004 | 2.58 | 0.35 | 1.58 | 0.22 | 1055 | Yes |
| Mexico | 2008 | 2.21 | 0.24 | 1.43 | 0.16 | 1635 | Yes |
| Mexico | 2010 | 2.64 | 0.32 | 1.64 | 0.2 | 1323 | Yes |
| Netherlands | 1990 | 3.75 | 0.33 | 1.38 | 0.12 | 2570 | Yes |
| Netherlands | 1993 | 4.16 | 0.38 | 1.23 | 0.11 | 2423 | Yes |
| Netherlands | 1999 | 4.21 | 0.37 | 1.27 | 0.11 | 2563 | Yes |
| Netherlands | 2004 | 3.41 | 0.18 | 1.36 | 0.07 | 7166 | Yes |
| Netherlands | 2007 | 3.17 | 0.16 | 0.98 | 0.05 | 8011 | Yes |
| Netherlands | 2010 | 3.63 | 0.18 | 1.37 | 0.07 | 8001 | Yes |
| Netherlands | 2013 | 3.62 | 0.18 | 1.3 | 0.07 | 7808 | Yes |
| Norway | 1979 | 1.8 | 0.1 | 1.71 | 0.1 | 6048 | No |
| Norway | 1986 | 5.11 | 0.45 | 1.89 | 0.17 | 2588 | Yes |
| Norway | 1991 | 3.83 | 0.2 | 1.76 | 0.09 | 7361 | Yes |
| Norway | 1995 | 3.45 | 0.17 | 1.14 | 0.06 | 8027 | Yes |
| Norway | 2000 | 3.18 | 0.13 | 0.88 | 0.04 | 11474 | Yes |

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| Norway | 2004 | 3.98 | 0.17 | 0.77 | 0.03 | 10947 | Yes |
| Norway | 2007 | 3.74 | 0.04 | 1.11 | 0.01 | 169708 | Yes |
| Norway | 2010 | 3.55 | 0.04 | 0.86 | 0.01 | 177229 | Yes |
| Norway | 2013 | 3.35 | 0.04 | 0.83 | 0.01 | 183146 | Yes |
| Peru | 2004 | 2.5 | 0.23 | 1.75 | 0.16 | 2463 | Yes |
| Peru | 2007 | 3.05 | 0.26 | 1.69 | 0.15 | 2667 | Yes |
| Peru | 2010 | 2.78 | 0.22 | 1.66 | 0.13 | 3239 | Yes |
| Peru | 2013 | 3.72 | 0.27 | 1.68 | 0.12 | 3930 | Yes |
| Russia | 2013 | 4.25 | 0.29 | 1.67 | 0.11 | 4360 | Yes |
| Russia | 2014 | 5.03 | 0.34 | 1.79 | 0.12 | 4412 | Yes |
| Russia | 2015 | 4.89 | 0.29 | 1.65 | 0.1 | 5752 | No |
| Russia | 2016 | 5.19 | 0.19 | 1.91 | 0.07 | 15716 | No |
| Slovakia | 2010 | 3.49 | 0.49 | 0.96 | 0.13 | 1024 | Yes |
| Slovakia | 2013 | 2.73 | 0.34 | 0.84 | 0.1 | 1289 | Yes |
| Slovenia | 2012 | 6.11 | 0.64 | 1.43 | 0.15 | 1841 | Yes |
| South Korea | 2006 | 4.67 | 0.32 | 1.69 | 0.11 | 4353 | No |
| South Korea | 2008 | 4.2 | 0.31 | 1.7 | 0.13 | 3616 | No |
| South Korea | 2010 | 4.38 | 0.36 | 1.62 | 0.13 | 3003 | No |
| South Korea | 2012 | 3.79 | 0.29 | 1.58 | 0.12 | 3329 | No |
| Spain | 1980 | 4.21 | 0.49 | 2.07 | 0.24 | 1503 | No |
| Spain | 1990 | 3.84 | 0.27 | 1.58 | 0.11 | 4036 | Yes |
| Spain | 1995 | 3.46 | 0.33 | 1.57 | 0.15 | 2250 | Yes |
| Spain | 2000 | 3.19 | 0.24 | 1.09 | 0.08 | 3549 | Yes |
| Spain | 2004 | 4.22 | 0.28 | 1.32 | 0.09 | 4433 | Yes |
| Spain | 2007 | 4.3 | 0.26 | 1.41 | 0.09 | 5327 | Yes |
| Spain | 2010 | 6.08 | 0.49 | 1.79 | 0.15 | 3043 | Yes |
| Spain | 2013 | 3.59 | 0.2 | 1.69 | 0.09 | 6681 | Yes |
| Spain | 2016 | 3.44 | 0.18 | 1.51 | 0.08 | 7451 | Yes |
| Sweden | 1975 | 3.93 | 0.2 | 1.54 | 0.08 | 7845 | Yes |
| Sweden | 1981 | 4.56 | 0.26 | 2.47 | 0.14 | 6092 | Yes |
| Sweden | 1987 | 4.71 | 0.24 | 1.77 | 0.09 | 7953 | Yes |
| Sweden | 1992 | 4.49 | 0.19 | 1.98 | 0.08 | 10824 | Yes |
| Sweden | 1995 | 3.97 | 0.16 | 1.63 | 0.07 | 11655 | Yes |
| Sweden | 2000 | 3.6 | 0.16 | 1.26 | 0.06 | 10319 | Yes |
| Sweden | 2005 | 3.15 | 0.13 | 1.07 | 0.04 | 11951 | Yes |
| Switzerland | 1982 | 2.05 | 0.14 | 1.34 | 0.09 | 4233 | Yes |
| Switzerland | 1992 | 3.55 | 0.24 | 1.3 | 0.09 | 4486 | Yes |

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| Switzerland | 2002 | 3.29 | 0.29 | 1.4 | 0.12 | 2646 | Yes |
| Switzerland | 2000 | 3.53 | 0.31 | 1.56 | 0.14 | 2578 | Yes |
| Switzerland | 2004 | 4.41 | 0.38 | 1.38 | 0.12 | 2648 | Yes |
| Switzerland | 2007 | 2.74 | 0.17 | 1.22 | 0.08 | 5057 | Yes |
| Switzerland | 2010 | 2.92 | 0.17 | 1.14 | 0.07 | 5759 | Yes |
| Switzerland | 2013 | 3.45 | 0.22 | 1.4 | 0.09 | 5097 | Yes |
| Taiwan | 1981 | 4.5 | 0.19 | 1.53 | 0.07 | 10635 | Yes |
| Taiwan | 1986 | 3.88 | 0.15 | 1.34 | 0.05 | 12864 | Yes |
| Taiwan | 1991 | 4.11 | 0.15 | 1.41 | 0.05 | 14978 | Yes |
| Taiwan | 1995 | 4.29 | 0.16 | 1.77 | 0.07 | 13619 | Yes |
| Taiwan | 1997 | 4.27 | 0.17 | 1.83 | 0.07 | 12572 | Yes |
| Taiwan | 2000 | 4.19 | 0.17 | 1.76 | 0.07 | 12301 | Yes |
| Taiwan | 2005 | 4.17 | 0.17 | 1.8 | 0.07 | 11903 | Yes |
| Taiwan | 2007 | 3.82 | 0.16 | 1.75 | 0.07 | 12042 | Yes |
| Taiwan | 2010 | 3.85 | 0.15 | 1.74 | 0.07 | 12748 | Yes |
| Taiwan | 2013 | 3.85 | 0.15 | 1.55 | 0.06 | 13300 | Yes |
| Taiwan | 2016 | 3.88 | 0.15 | 1.66 | 0.06 | 13648 | Yes |
| UK | 1969 | 3.73 | 0.26 | 1.11 | 0.08 | 4102 | Yes |
| UK | 1974 | 3.56 | 0.27 | 1.35 | 0.1 | 3547 | Yes |
| UK | 1979 | 5.03 | 0.34 | 1.34 | 0.09 | 4280 | Yes |
| UK | 1986 | 4.48 | 0.3 | 1.79 | 0.12 | 4515 | Yes |
| UK | 1991 | 3.56 | 0.24 | 1.69 | 0.11 | 4445 | Yes |
| UK | 1994 | 3 | 0.11 | 1.42 | 0.05 | 15751 | Yes |
| UK | 1995 | 3.21 | 0.22 | 1.48 | 0.1 | 4091 | Yes |
| UK | 1999 | 2.89 | 0.1 | 1.4 | 0.05 | 15200 | Yes |
| UK | 2004 | 2.7 | 0.09 | 1.27 | 0.04 | 17314 | Yes |
| UK | 2007 | 2.87 | 0.1 | 1.34 | 0.05 | 15272 | Yes |
| UK | 2010 | 2.57 | 0.12 | 1.34 | 0.06 | 9839 | Yes |
| UK | 2013 | 2.79 | 0.14 | 1.5 | 0.08 | 7715 | Yes |
| UK | 2016 | 2.49 | 0.13 | 1.32 | 0.07 | 7340 | Yes |
| US | 1974 | 3.86 | 0.23 | 1.51 | 0.09 | 5558 | Yes |
| US | 1979 | 3.7 | 0.08 | 1.46 | 0.03 | 44749 | Yes |
| US | 1986 | 3.36 | 0.08 | 1.64 | 0.04 | 38274 | Yes |
| US | 1991 | 3.45 | 0.08 | 1.54 | 0.04 | 38875 | Yes |
| US | 1994 | 2.43 | 0.06 | 1.45 | 0.03 | 37355 | Yes |
| US | 1997 | 2.29 | 0.06 | 1.47 | 0.04 | 30913 | Yes |
| US | 2000 | 2.19 | 0.05 | 1.4 | 0.03 | 46961 | Yes |

Table 3: Hypothesis testing of $\widehat{\alpha}_{\text{lab}} = \widehat{\alpha}_{\text{cap}}$.

| Country | Year | $\widehat{\alpha}_{\text{lab}}$ | s.e. | $\widehat{\alpha}_{\text{cap}}$ | s.e. | $N$ | Reject $H_0$? |
|---|---|---|---|---|---|---|---|
| US | 2004 | 2.39 | 0.05 | 1.33 | 0.03 | 42354 | Yes |
| US | 2007 | 2.34 | 0.05 | 1.49 | 0.03 | 39315 | Yes |
| US | 2010 | 2.56 | 0.06 | 1.41 | 0.03 | 37388 | Yes |
| US | 2013 | 2.4 | 0.07 | 1.4 | 0.04 | 24494 | Yes |
| US | 2016 | 2.29 | 0.05 | 1.42 | 0.03 | 45401 | Yes |
| Uruguay | 2004 | 2.53 | 0.32 | 1.81 | 0.23 | 1241 | No |
| Uruguay | 2007 | 3.26 | 0.22 | 1.53 | 0.11 | 4236 | Yes |
| Uruguay | 2010 | 3.1 | 0.22 | 1.63 | 0.11 | 4085 | Yes |
| Uruguay | 2013 | 3.69 | 0.28 | 1.8 | 0.14 | 3497 | Yes |
| Uruguay | 2016 | 3.53 | 0.26 | 1.69 | 0.13 | 3632 | Yes |
| Vietnam | 2011 | 3.26 | 0.4 | 1.23 | 0.15 | 1362 | Yes |
| Vietnam | 2013 | 2.61 | 0.31 | 1.64 | 0.2 | 1384 | No |

Note: $\widehat{\alpha}_{lab}$ *(resp.* $\widehat{\alpha}_{cap}$*): point estimate of Pareto exponent for labor (resp. capital) income; s.e.: standard error (calculated using the inverse Fisher information); $N$: the number of positive capital income observations; the last column denotes if $H_0$ is rejected.*