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# Capital and Labor Income Mobility\*

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## Abstract

Does capital or labor income drive overall relative income mobility? This article examines the dynamics of capital and labor *intra*-generational income mobility, utilizing individual-level income registers from Norway covering 293,875 individuals observed over 26 years. It introduces a novel methodological framework to decompose total income mobility into the contributions of its components across the life cycle. We present *three* key findings on the subject. *First*, different capital and labor income mobility measures along the respective unidimensional distributions do not convey clear income-factor mobility orderings. *Second*, upward total income mobility is mainly driven by upward labor income mobility and by the joint upward mobility of capital and labor. *Third*, downward total income mobility is mainly driven by downward capital income mobility and by the joint downward mobility of capital and labor. These results are robust to considering only high upward or downward jumps and are discussed in light of recent theoretical and empirical findings on the dynamics of compositional inequality and homoploutia in capital and labor.

**JEL-Classification:** D31, D33, D63.

**Keywords:** Income mobility decomposition; Capital–labor income dynamics; Intra-generational relative mobility.

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# 1 Introduction

The study of income dynamics is a central topic in economics. Income can be derived from labor or from the ownership of assets (wealth) that generate returns. Individual income trajectories can, therefore, be decomposed into factors influenced by labor and capital market dynamics. But which of these primarily drives relative income mobility — the degree to which individuals or households change their position within the income distribution over time — in modern economies: labor income or capital income? While factor shares have received increasing attention in recent decades, and have been described as the principal problem of political economy (Atkinson, 2009), their intersection with the study of income mobility has been largely overlooked.

To address the above questions, this paper develops a measurement framework that decomposes the relative total income mobility into its components of labor and capital income. To our knowledge, this is the first such decomposition in the economic literature. This framework enables a classification of mobility types based on factor incomes by decomposing standard measures of relative upward and downward total income mobility. Specifically, we decompose total income mobility and examine the frequency of *four* key mobility types that shape overall relative mobility patterns: (i) upward capital income mobility only, (ii) upward labor income mobility only, (iii) simultaneous upward capital and labor mobility, and (iv) simultaneous downward capital and labor mobility.

The *first* and *second* types describe upward jumps along the capital and labor income distributions, respectively. The *third* and *fourth* types describe joint upward and downward jumps along both distributions of capital and labor income. We refer to the first two as *capital-* and *labor-driven* upward mobility, and the third and fourth as upward and downward *homoploutic* mobility, respectively. This paper then applies this framework to an intra-generational panel using high-quality register data from Norway covering 293,875 individuals observed over 26 years. The Norwegian administrative data provide an optimal setting to minimize measurement error and

offer a clean empirical context for analyzing mobility patterns.

We document three main findings. *First*, different capital and labor income mobility measures along the respective uni-dimensional distributions do not convey clear income-factor mobility orderings - depending on what each mobility indicator emphasizes, capital or labor income mobility is higher. However, aggregate measures may mask different mobility patterns, as rank is not held constant across distributions. *Second*, upward total income mobility is primarily driven by upward labor income mobility and the joint upward mobility of labor and capital. *Third*, downward total income mobility is mainly driven by downward capital income mobility and the joint downward mobility of labor and capital. While we expected the joint dynamics of capital and labor mobility to play a significant role in shaping overall total income mobility, our results reveal that when analyzed separately, labor income tends to lift individuals up the total income ladder, whereas capital income tends to push them down. Although this effect is less pronounced for large upward or downward movements (e.g., transitions from the bottom or top 10% to the top or bottom 10%), the findings remain robust across different specifications.

The asymmetry that we observe between labor and capital mobility can be explained by the different underlying dynamics of these income sources. Labor income growth is often tied to systematic life-cycle mechanisms, such as career progression and human capital accumulation, which tend to generate upward movements in the distribution. By contrast, capital incomes are highly concentrated, volatile, and exposed to negative shocks, such as losses in financial markets or business failures. While some individuals experience large positive returns, these are less frequent in the aggregate. As a result, capital income mobility is more often associated with downward movements, whereas labor income is more often associated with upward shifts. This is also the result of a high level of compositional inequality, namely that capital income represents a larger share of total income at the top, whereas labor income is the dominant source for most of the population ([Ranaldi and Milanovic, 2022](#), [Iacono and Palagi, 2022](#)). All in all, while upward mobility can in principle stem from both factors, we observe it is primarily driven by labor income or by the joint dynam-

ics of labor and capital, but almost never by capital alone. In other words, sustained upward movement typically requires labor income, which then allows individuals to accumulate and benefit from capital as well.

These findings connect with and extend the existing literature on economic mobility, which has paid relatively little attention to the joint dynamics of capital and labor incomes, potentially due to poorer data quality regarding capital incomes at the top of the distribution. Specifically, this paper contributes to *four* streams of research, which we discuss below.

**Literature** First, this paper contributes to the broader literature on economic mobility by offering a novel angle of investigation: it focuses on intra-generational mobility and its decomposition by income sources, using high-quality Norwegian register data. This perspective complements the more traditional focus on inter-generational mobility (Jäntti and Jenkins, 2015). Recent trends in inter-generational economic mobility in Norway are documented in depth by Markussen and Røed (2020), who find stable or mildly declining rank–rank mobility for sons in the post-war period, but a marked decline for daughters. A portion of the overall decline in mobility has been attributed to the sustained immigration inflows observed over recent decades (Hoen et al., 2022).<sup>1</sup>

The results of this paper are also connected to the recent theoretical and empirical literature on *compositional inequality* and *homoploutia*, which examine the composition of capital and labor incomes across the entire income distribution and the top of the distribution, respectively, both within countries and globally. Specifically, in line with recent findings on the rising tendency of homoploutia - the proportion of individuals in the top deciles of both the capital and labor income distributions - in the US (Berman and Milanovic, 2024), we also find that the joint dynamics of capital and labor income mobility is a key driver of upward social mobility. Moreover, our finding that labor income contributes more to total income mobility than capital income aligns with recent evidence showing that, at a global level, labor income - rather than

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<sup>1</sup>For longer-run trends in intergenerational mobility in Norway, see Modalsli (2017).

capital income - is the primary determinant of total income status ([Ranaldi, 2025](#)).

Our results relate as well to the literature on innovation and income dynamics. [Aghion et al. \(2019\)](#), for instance, show that innovation increases top income inequality, primarily through labor income gains for individuals linked to successful firms. While their analysis focuses on cross-sectional inequality at the top, our finding that upward mobility is mainly driven by labor income and joint gains in labor and capital is consistent with innovation-driven dynamics. However, unlike [Aghion et al. \(2019\)](#), we find that downward mobility is more strongly associated with declines in capital income, pointing to a broader set of mechanisms shaping income trajectories.

Finally, our work offers novel insights into the public economics literature on the relationship between mobility and taxation. If a social planner aims to enhance relative income mobility, it is essential to determine which of the different income factors yields a higher degree of mobility. This distinction can help guide policies, such as differential taxation of income sources, to achieve the desired mobility outcomes.<sup>2</sup> Notice that although the relationship between intra-generational mobility and welfare can be ambiguous, in our setting we assume that higher mobility is desirable, as it is associated with lower income dispersion across the life-cycle ([Jäntti and Jenkins, 2015](#), [Cappelen et al., 2024](#)).<sup>3</sup>

The paper is structured as follows. Section 2 presents the data and introduces the mobility measures for capital and labor income distributions, analyzed separately. Section 3 outlines the methodology developed to decompose total income mobility into the contributions of capital and labor. Furthermore, it offers a methodological discussion on the relationship between income mobility and compositional inequality, specifically in terms of capital and labor income. Section 4 conveys the main results from the analysis. Section 5 presents some additional analysis, while section 6 concludes the paper.

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<sup>2</sup>For a more detailed discussion of the relationship between tax rates and income mobility in Norway, see [Cappelen et al. \(2024\)](#). They find a negative relationship between income mobility and marginal tax rates, implying that taxation of both capital and labor income reduces income mobility.

<sup>3</sup>To gauge more understanding of why lifetime income inequality can be more relevant than the distribution of current income, see [Aaberge and Mogstad \(2015\)](#).

## 2 Descriptive statistics and mobility measures

Our analysis uses an intra-generational panel assembled from the universe of annual individual income tax return records maintained by Statistics Norway, covering the period 1993–2018 (26 annual waves). We study the 1960–1964 birth cohorts, which we can follow annually in the tax-register data from ages 2933 (in 1993) through ages 5458 (in 2018). Focusing on these cohorts yields the longest contiguous panel of adult income trajectories available in our sample period.

To construct a strictly balanced panel, we impose sample restrictions that ensure each individual is observed in every year from 1993 to 2018. Specifically, we exclude individuals who (i) die, (ii) emigrate, or (iii) have missing information in any year within the observation window. The resulting balanced panel contains 7,640,750 person-year observations, corresponding to 293,875 individuals observed for 26 consecutive years. The sample is evenly split by sex: 148,419 men (50.5%) and 145,456 women.

**Income definition** We measure income mobility using annual individual gross pre-tax market income, defined as the sum of wage and salary earnings, self-employment income, and capital income, excluding all government transfers. Given our interest in the interaction between capital–labor income dynamics and mobility, we decompose market income into two components: labor income and capital income.

Capital Income (CI, hereafter) is defined as the pre-tax sum of interest received, share dividends, realized capital gains (or losses), and other property income received during the calendar year. Additionally, CI includes net income from renting land and other fixed capital not classified under self-employment income, profits from life insurance savings schemes, capital income from abroad, and other unspecified property income.

Labor Income (LI, hereafter) is defined as the sum of employee earnings and net self-employment income received during the calendar year. In our baseline estimation, we classify net self-employment income as part of work income, which is an

arbitrary but necessary decision.<sup>4</sup> Total income is obtained by summing capital income and labor income.<sup>5</sup>

## 2.1 Descriptive statistics

This subsection reports descriptive statistics for the three univariate distributions in Table 1. Labor income is the primary component of market income: its sample mean is approximately twelve times larger than the mean of capital income. In contrast, the distribution of capital income exhibits substantially greater dispersion and right-skewness than the distribution of labor income, as reflected in its higher upper-tail quantiles. In particular, capital income is close to zero for at least three quarters of observations, yet the maximum observed value of capital income is nearly an order of magnitude larger than the maximum labor income.

Table 1: Descriptive statistics

	Capital Income (CI)	Labor Income (LI)	Total Income (TI)
Mean	3974.66	50001.79	54225.69
Std.Dev	165526.9	56613.53	193985.23
Q1	11.60	26592.64	27394.08
Median	91.60	46479.65	47302.32
Q3	504.28	65193.93	66998.79
Max	339603552	45582364	338992800
Skewness	1261.496	219.88	998.77
Kurtosis	2382002	145469.82	1532710.55
N (obs)	7640750	7640750	7640750

*Note:* Descriptive statistics for the three univariate distributions. Reported moments include the mean, standard deviation, minimum, first quartile (Q1), median, third quartile (Q3), maximum, coefficient of variation, skewness, kurtosis, and the number of observations. All monetary values are expressed in constant U.S. dollars (index: 2019=100). The Consumer Price Index (CPI) has been sourced from <https://data.oecd.org/price/inflation-cpi.htm>, while exchange rates for the period 1993 – 2018 have been obtained from <https://data.oecd.org/conversion/exchange-rates.htm>.

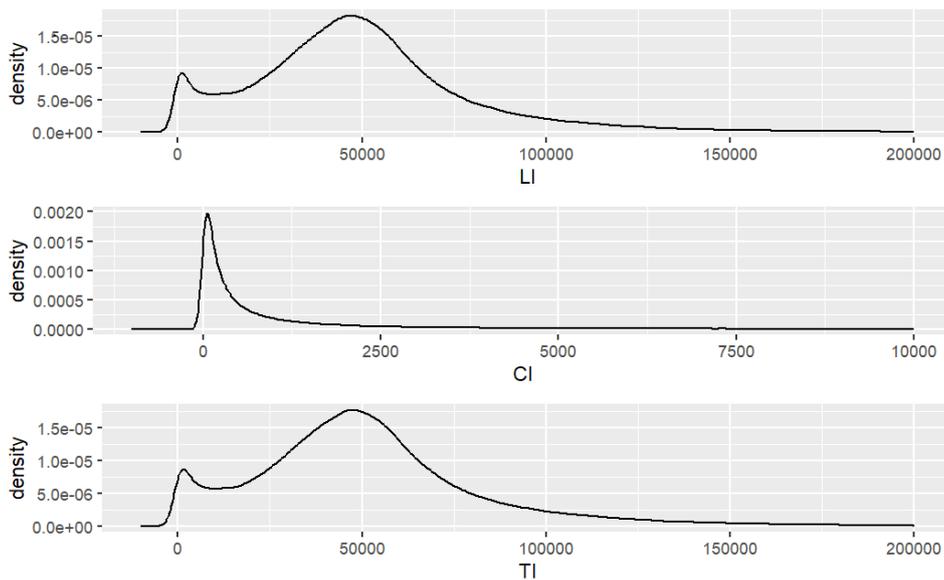
To start assessing whether the pronounced differences across income components reflect more than life-cycle variation or other time-series dynamics, we examine the

<sup>4</sup>We conduct a robustness check on this income definition in subsection 5.1.

<sup>5</sup>All income values are adjusted for inflation using the Consumer Price Index (CPI) and expressed in 2019 USD. The CPI data and exchange rates for the period 1993–2018 are sourced from the OECD (see [CPI data](#) and [exchange rates](#)).

cross-sectional distributions of within-person average incomes. Specifically, for each individual  $i$  we compute mean total income over the full observation window, and analogously for LI and CI. Figure 1 plots kernel density estimates of these three univariate distributions (note the different horizontal scales across panels). The distribution of average labor income is concentrated approximately between USD 20,000 and 75,000, whereas the distribution of average capital income features substantial mass near zero for the majority of individuals.

Figure 1: Univariate densities - LI, CI, TI



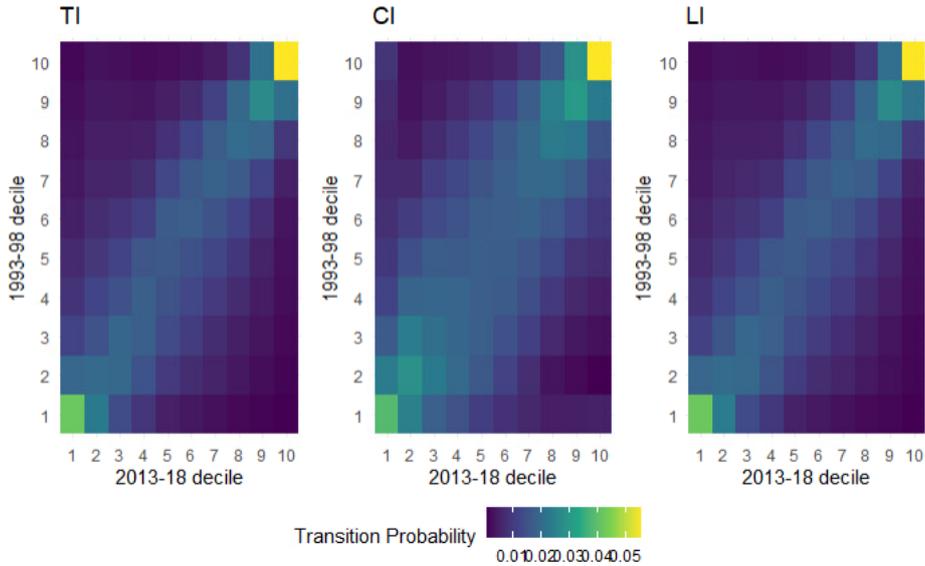
*Note:* this figure plots univariate kernel density estimates for average labor income (top panel), capital income (middle panel), and total income (bottom panel). For each of the 293,875 individuals in the balanced sample, we compute the within-person time average of capital income (CI), labor income (LI), and total income (TI) over the full observation window, 1993–2018.

To complement the evidence of this subsection, Appendix A presents a set of statistics on the joint dynamics of the capital and labor income distributions across the life cycle. Specifically, it traces the trajectories of *homoploutia* (Berman and Milanovic, 2024) and compositional inequality (Ranaldi, 2022) in capital and labor by describing these trends, for the first time, over the life cycle rather than cross-sectionally.

## 2.2 Mobility measures

For convenience, we divide the time period into two intervals: 1993 – 1998 as the initial period and 2013 – 2018 as the final period. We then observe mobility in this two-period case. Following [Atkinson \(1981\)](#), consider there are 10 deciles. The relative number of observations in decile  $k$  in period  $t$  is denoted by  $m_t^k$  with  $(k = 1, \dots, 10; t = 1, 2)$ . The marginal distribution in period 1 is summarized by the vector  $m_1^k = (m_1^1, m_1^2, \dots, m_1^{10})$ , and similarly for period 2. Hence, as shown in [Jäntti and Jenkins \(2015\)](#), the relationship between the two periods is given by  $m_1^k = m_2^k A$ . In this context, mobility is entirely characterized by the transition matrix  $A$ . To begin with, we compute the transition matrix  $A$  for each of the three univariate distributions, namely total income, capital income, and labor income. These transition matrices are presented in figure 2.

Figure 2: Decile Transition Matrix - TI, CI, LI

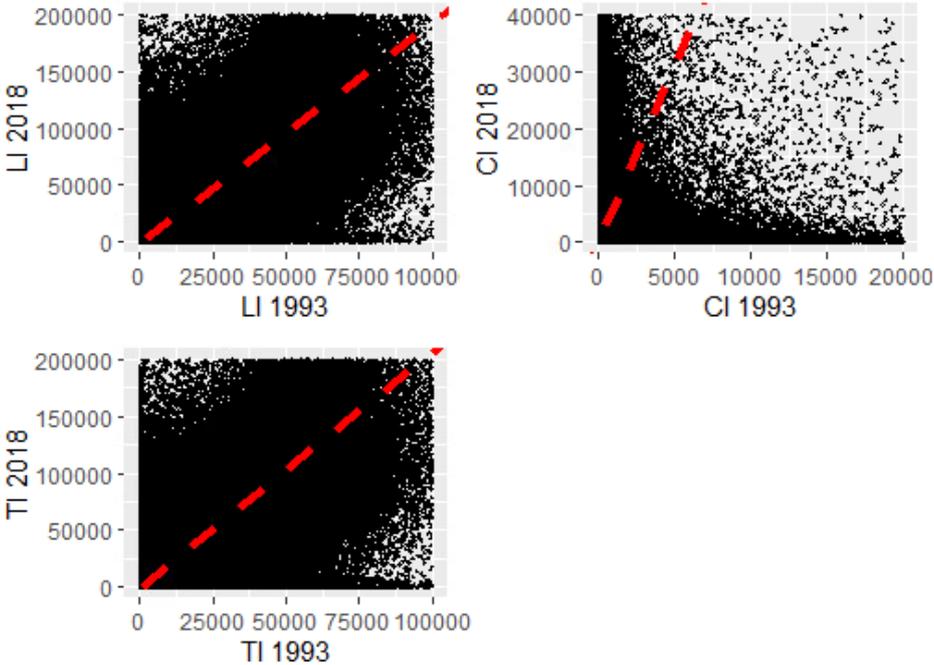


*Note:* Recall that we divide the entire time period into two intervals: pooling 1993 – 1998 as the initial period and 2013 – 2018 as the final period. Darker blue indicates a lower transition probability, implying that the cell contains fewer observations. Lighter green and yellow correspond to increasing transition probabilities, suggesting that a significant portion of individuals is in these cells.

A complementary visualization of relative mobility in a two-period setting is the bivariate joint distribution of incomes across time. We represent this joint distribution

using scatter plots of individual incomes (LI, CI, TI), in the final year [2018] against the corresponding values in the initial year [1993]. Figure 3 reports the resulting three panels, one for each income concept. The red line provides a benchmark based on mean growth in the relevant income category. Observations above (below) the line correspond to individuals whose income increased by more (less) than the change in the category-specific mean between 1993 and 2018. A tight clustering of points around the benchmark indicates relatively limited heterogeneity in income growth (lower relative mobility), whereas greater dispersion around the line indicates larger heterogeneity in growth rates (higher relative mobility).

Figure 3: Scatterplots - LI, CI, TI



*Note:* The slope of the dashed line corresponds to the change in mean income in the relevant category between 1993 and 2018. Observations above (below) the red line represent individuals whose income (LI, CI, TI) increased by more (less) than the corresponding change in the category-specific mean over the same period.

We find that, especially for CI, many observations lie far from the benchmark line. This pattern is likely driven in part by life-cycle dynamics in asset accumulation: early in adulthood, many individuals report capital income that is zero or close to zero because they have not yet accumulated substantial wealth. In the absence of inheri-

tances (or other large inter-vivos transfers), positive capital income typically requires a pre-existing capital stock, which for many individuals is built only gradually over the life cycle.

To implement the log transformation required for the mobility indices, we address non-positive realizations of each income component. Specifically, for each factor-income variable we replace non-positive values with 1, so that the log transformation is well defined for all observations.<sup>6</sup> The resulting dataset therefore contains the same number of person-year observations as in the previous subsections. Table 2 reports the corresponding set of mobility indices.

Table 2: Mobility indices

	Capital Income (CI)	Labor Income (LI)	Total Income (TI)
Prais-Bibby	0.749	0.509	0.262
Beta	0.716	0.767	0.562
SD period-1	1.568	1.924	2.259
SD period-2	2.291	3.202	2.676
SD ratio	0.685	0.601	0.844
Pearson's $r$	0.491	0.461	0.474
Shorrocks index	0.832	0.836	0.906

*Note:* Table 2 reports a set of mobility indices for the three univariate income distributions: capital income (CI), labor income (LI), and total income (TI). Recall that we partition the sample into two multi-year periods to mitigate transitory fluctuations, pooling 1993–1998 as the initial period and 2013–2018 as the terminal period.

We begin with the Prais–Bibby index, a rank-based measure of mobility that quantifies the extent to which individuals move across income classes (e.g., deciles or quintiles) between two periods. The index ranges from 0 (perfect immobility) to 1 (perfect mobility) (Prais, 1955, Bibby, 1975).

The Prais–Bibby index indicates substantially higher mobility in CI (0.749) than in LI (0.509). Next, we estimate  $\beta$ , the OLS coefficient capturing the association between log income in period 2 and log income in period 1.  $\beta$  indicates a higher persistence between the two periods for LI (0.767 > 0.716), implying again lower mobility com-

<sup>6</sup>This transformation affects only observations with non-positive values and leaves the sample size unchanged.

pared to CI. Dispersion in the univariate distributions is summarized by the standard deviations in period-1 and period-2, and the SD ratio. A lower SD ratio for LI implies a larger proportional increase in dispersion between periods than for CI.

$\beta$  and the SD ratio are used to compute Pearson's  $r = \beta \times \frac{\sigma_1}{\sigma_2}$ , which corresponds to  $\beta$  scaled by the changes in dispersion in the univariate distributions. Pearson's  $r$  is an index of immobility, with  $r = 1$  implying unchanged ranks and hence total immobility. As shown in Table 2, Pearson's  $r$  is lower for LI (0.461), indicating higher mobility than for CI (0.491), which contradicts the evidence of the  $\beta$  and the Prais-Bibby index. Finally, similarly to Pearson's  $r$ , the Shorrocks index (Shorrocks, 1978) indicates slightly higher mobility for LI.

In sum, the mobility indices computed on the univariate distributions of CI and LI do not deliver an unambiguous ordering of income-factor mobility: depending on the metric and the aspect of mobility it emphasizes (e.g., re-ranking, persistence, or changes in dispersion), capital income may appear more mobile than labor income, or vice versa. Therefore, in the next section we adopt an alternative approach that takes total income as the relevant welfare metric and decomposes total-income mobility into the contributions of its constituent factors.

### 3 Methodology

This section presents a framework for decomposing total income mobility across the life cycle into its capital and labor income components. It begins with a simple extension of a standard social welfare framework to theoretically underpin the main dynamics at play, and then decomposes inter-temporal income jumps to allow for the assessment of the various income components. Further discussion on the methodological relationship between compositional inequality and income mobility will follow. In Appendix B, we complement this empirical structure with a probabilistic setup that formalizes the same objects in rank space: transition matrices and decomposition shares are shown to be probability masses over regions of a temporal dependence structure in ranks.

### 3.1 Social welfare framework

Social welfare,  $W$ , in a two-period context, can be defined as follows (Atkinson and Bourguignon, 1982, Jäntti and Jenkins, 2015):

$$W = \int_0^{\alpha_y} \int_0^{\alpha_x} U(x, y) f(x, y) dx dy, \quad (1)$$

where  $U(x, y)$  is a differentiable utility function of income at time  $t$ ,  $x$ , and at time  $t + 1$ ,  $y$ ;  $f(x, y)$  is the bivariate joint density; and  $\alpha_x$  and  $\alpha_y$  represent the maximum incomes at time  $t$  and  $t + 1$ , respectively. The relationship between the two distributions,  $x$  and  $y$ , as represented by the density function  $f$ , can be interpreted as the mobility of the population.<sup>7</sup>

To incorporate the composition of income into the social welfare function, equation (1) can be re-written as:

$$W = \int_0^{\alpha_{y1}} \int_0^{\alpha_{y2}} \int_0^{\alpha_{x1}} \int_0^{\alpha_{x2}} U(\mathcal{V}(x_1, x_2), \mathcal{V}(y_1, y_2)) f(x_1, x_2, y_1, y_2) dx_1 dx_2 dy_1 dy_2, \quad (2)$$

where the subscripts 1 and 2 refer to the two income components of the respective income distributions. This function assumes that preferences between the two income components remain constant over time, as the form of  $\mathcal{V}$  is unchanged across periods. However, an alternative formulation that relaxes this assumption could be written as follows:

$$U(\mathcal{V}_t(x_1, x_2), \mathcal{V}_{t+1}(y_1, y_2)).$$

While it is straightforward to assume that increases in income during either period are desirable for all income sources ( $\frac{dU}{dx_i}, \frac{dU}{dy_i} \geq 0 \forall i$ ), assessing the degree of substitutability and complementarity between income sources across time is more challenging. In the next section, we present a decomposition framework to precisely assess the separate contributions of the different income components to overall income mobility. Through the empirical analysis of capital and labor income mobility in Norway, this paper aims to shed light on these issues.

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<sup>7</sup>In the probabilistic setup (Appendix B), this same idea is made explicit by separating marginal distributions from dependence: once outcomes are expressed in ranks, mobility is driven by how dependence reallocates probability mass across origin–destination transitions.

### 3.2 Inter-temporal income jumps

Consider a population of  $n$  individuals, each with an income  $y_i^t \in \mathfrak{X} \subseteq \mathbb{R}_+$ , where  $i = 1, \dots, n$  at time  $t$ . Individual income is composed of capital income  $\pi_i^t$  and labor income  $w_i^t$ , such that  $y_i^t = \pi_i^t + w_i^t$ .<sup>8</sup> The cumulative distribution function  $F(x)$  represents the proportion of the population with an income less than or equal to  $x$ , while its inverse, the quantile function  $Q(p)$ , identifies the income thresholds for given quantiles. If  $F(x)$  is absolutely continuous, its density function  $f(x)$  is the derivative of  $F(x)$ . In what follows,  $F_t(y_i^t)$  plays the role of an individual's *baseline rank* (a percentile position) at time  $t$ , which is precisely the object that the probabilistic setup uses to connect individual jumps to transition probabilities in rank space (Appendix B).

The income thresholds corresponding to the quantiles above and below a given income  $y$  are defined as  $Q^+(F(y))$  and  $Q^-(F(y))$ , respectively. The gaps between an individual's income at time  $t+1$  and these quantile thresholds relative to their income at time  $t$  are expressed as:

$$\epsilon(y_i^{t+1}) = y_i^{t+1} - Q_{t+1}^+(F_t(y_i^t)), \quad (3)$$

Thus,  $\epsilon(y_i^{t+1})$  compares realized income at  $t+1$  to the counterfactual income threshold corresponding to the *same rank* held at  $t$ , so that mobility is measured as a deviation from “staying put” in the distribution.

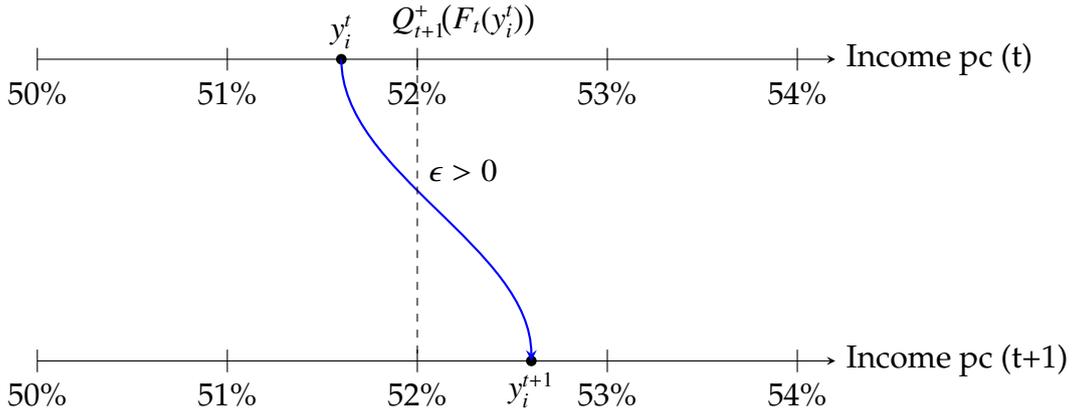


Figure 4: Positive total income jump.

<sup>8</sup>Throughout, lowercase letters denote individual realizations of the corresponding random variables used in Appendix B.

Figures 4 and 5 illustrate a positive and negative total income jumps, respectively.

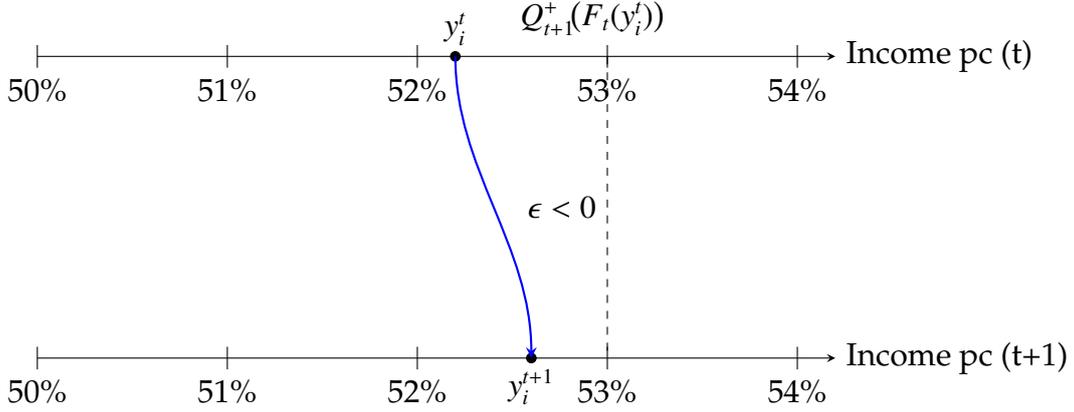


Figure 5: Negative total income jump.

Equation 3 allows for evaluating whether an individual's income has risen above or fallen below the upper quantile threshold. Specifically, if  $\epsilon > 0$ , individual  $i$ 's income has risen above the upper quantile threshold of the distribution at time  $t + 1$ , relative to their income at time  $t$ , moving up by at least one quantile. If  $\epsilon < 0$ , individual  $i$ 's income has either fallen by at least one quantile or remained below the upper quantile threshold of the distribution at time  $t + 1$ , relative to their income at time  $t$ .<sup>9</sup>

To account for the contributions of capital and labor income components in the dynamics of total income, equation (3) can be decomposed as follows:

$$\epsilon(y_i^{t+1}) = \underbrace{\epsilon_\pi(\pi_i^{t+1})}_{\text{capital jump}} + \underbrace{\epsilon_w(w_i^{t+1})}_{\text{labor jump}} + \underbrace{\left(-Q_{t+1}(F_t(y_i^t)) + Q_{t+1}(F_{\pi,t}(\pi_i^t)) + Q_{t+1}(F_{w,t}(w_i^t))\right)}_{\text{alignment coefficient}}, \quad (4)$$

where  $\epsilon_\pi(\pi_i^{t+1})$  and  $\epsilon_w(w_i^{t+1})$  represent the quantile gap changes due to  $\pi$  and  $w$  compo-

<sup>9</sup>Aggregating these individual events across the population yields the empirical transition matrix; in Appendix B.2 the same objects are written as probabilities (integrals) over regions of the rank-transition space induced by the temporal copula.

nents, respectively.<sup>10</sup> Formally, we can write:

$$\begin{aligned}\epsilon_\pi(\pi_i^{t+1}) &= \pi_i^{t+1} - Q_{t+1}(F_{\pi,t}(\pi_i^t)) \\ \epsilon_w(w_i^{t+1}) &= w_i^{t+1} - Q_{t+1}(F_{w,t}(w_i^t)).\end{aligned}$$

This decomposition has a direct rank-based interpretation:  $\epsilon_\pi$  and  $\epsilon_w$  correspond to component-specific rerankings between  $t$  and  $t+1$ , while  $B$  captures how contemporaneous dependence between  $(\pi, w)$  affects the mapping from component ranks to the total-income rank.

The term  $B = -Q_{t+1}(F_t(y_i^t)) + Q_{t+1}(F_{\pi,t}(\pi_i^t)) + Q_{t+1}(F_{w,t}(w_i^t))$  quantifies the alignment of total income  $y$ , capital income  $\pi$ , and labor income  $w$  across their respective distributions. If the distribution functions  $F$ ,  $F_\pi$ , and  $F_w$  are identical and the three variables are perfectly rank-aligned,  $B$  equals zero.

The notion of alignment embedded in  $B$  can be formalized more rigorously as a statement about the admissible dependence structures linking capital and labor income ranks. Given fixed marginal distributions, the joint distribution of  $(\pi, w)$  is not unique and is constrained by *Fréchet–Hoeffding bounds*, which characterize the set of feasible mappings between component ranks and total income ranks. These bounds define extremal cases ranging from perfect positive alignment (*co-monotonicity*) to maximal negative association (*counter-monotonicity*), each implying different benchmark positions for  $F_t(y_i^t)$  and therefore for the future reference threshold  $Q_{t+1}(F_t(y_i^t))$ . From this viewpoint, the alignment coefficient can be interpreted as measuring where the observed economy lies within this feasible region. A formal derivation of these envelopes, together with an operational normalization of alignment within the Fréchet set, is provided in Appendix C.

The figures below illustrate this decomposition under the assumption that the

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<sup>10</sup>Equation (4) can be rewritten relatively to the quantile threshold, as follows:

$$\tilde{\epsilon} = \frac{\epsilon(y_i^{t+1})}{Q_{t+1}(F_t(y_i^t))} = \frac{\epsilon_\pi}{Q_{t+1}(F_t(\pi_i^t))} \frac{Q_{t+1}(F_t(\pi_i^t))}{Q_{t+1}(F_t(y_i^t))} + \frac{\epsilon_w}{Q_{t+1}(F_t(w_i^t))} \frac{Q_{t+1}(F_t(w_i^t))}{Q_{t+1}(F_t(y_i^t))} + \underbrace{\frac{B}{Q_{t+1}(F_t(y_i^t))}}_{\tilde{B}}.$$

alignment coefficient has no impact — a premise consistent with the empirical evidence presented in the next section.

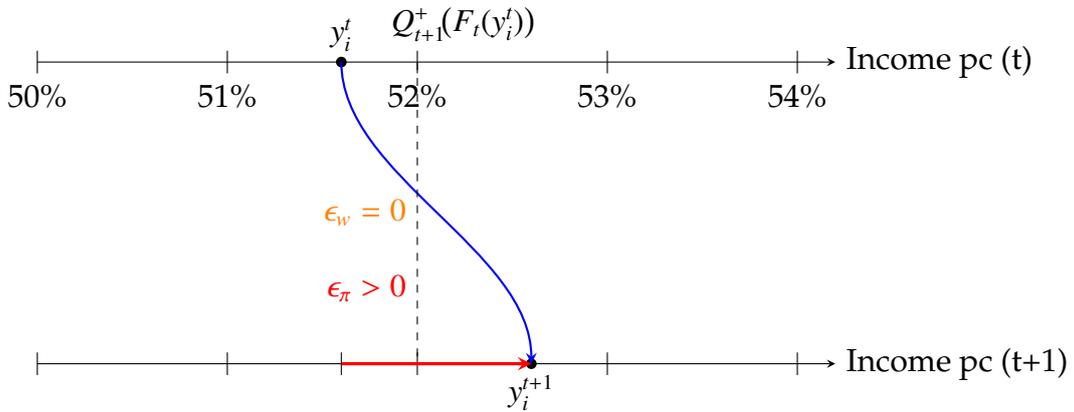


Figure 6: Positive **capital** jump and zero **labor** jump. The alignment coefficient is assumed to have no impact (in line with empirical findings).

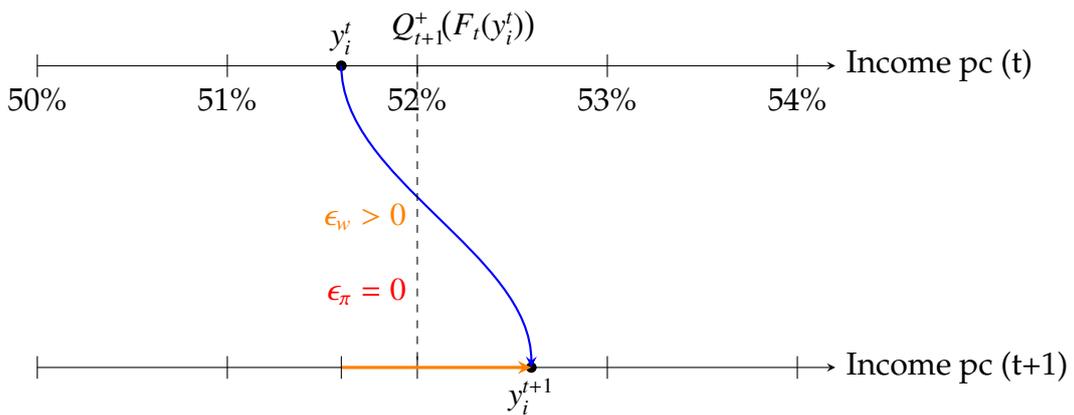


Figure 7: Positive **labor** jump and zero **capital** jump. The alignment coefficient is assumed to have no impact (in line with empirical findings).

Quantile functions for total income, capital income, and labor income are related in the following way:

$$Q_y(p) = \alpha Q_\pi(p) + \beta Q_w(p), \quad (5)$$

where  $\alpha = \frac{\pi_{r_{Q_y(p)}}}{Q_\pi(p)}$  and  $\beta = \frac{w_{r_{Q_y(p)}}}{Q_w(p)}$ , with  $r_{Q_y(p)}$  indicating ranking with respect to  $y$ , represent coefficients capturing the relative contributions of capital and labor income to the  $p$ th quantile of total income. These coefficients may deviate from one, indicating

disproportionate contributions of capital or labor income relative to their respective distributions.

While equation (5) can be evaluated for each period  $t$ , we can slightly modify the equation to explicitly incorporate an inter-temporal interpretation of the main coefficients  $\alpha$  and  $\beta$ , as follows:

$$Q_{y,t+1}(p) = \alpha^* Q_{\pi,t}(p) + \beta^* Q_{w,t}(p), \quad (6)$$

where  $\alpha^* = \frac{\pi_r Q_{y,t+1}(p)^{t+1}}{Q_{\pi,t}(p)}$  and  $\beta^* = \frac{w_r Q_{y,t+1}(p)^{t+1}}{Q_{w,t}(p)}$  represent the inter-temporal contributions of capital and labor income, respectively, to total income ranking status at time  $t + 1$ .

### 3.3 Mobility decomposition measures

This subsection presents the main aggregate measures of income mobility decomposition in terms of capital and labor. It builds on the previously derived decomposition of inter-temporal income gaps while also decomposing widely used measures of income mobility.

#### 3.3.1 Matrix decomposition

To formalize transitions between income quantiles over time, let us define the following transition matrix  $M$ :

$$M := \begin{bmatrix} m_{11} & m_{12} & \dots & m_{1n} \\ m_{21} & m_{22} & \dots & m_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n1} & m_{n2} & \dots & m_{nn} \end{bmatrix}, \quad (7)$$

where  $m_{ij} = \frac{|M_{ij}|}{n}$  represents the proportion of individuals transitioning from quantile  $i$  of the total income distribution at time  $t$  to quantile  $j$  of the total income distribution at time  $t + 1$ . Equivalently,  $m_{ij}$  is the sample analogue of the probability  $\mathbb{P}(R_{Y,t} = i, R_{Y,t+1} = j)$  in rank space; the probabilistic setup shows that these probabilities can be expressed as integrals of the rank-transition dependence over origin-destination regions (Appendix B.3). This matrix can be decomposed to identify specific mobility patterns influenced by components such as  $\epsilon_{\pi}$ ,  $\epsilon_w$ , and  $B$ .

The matrix  $M$  can in fact be decomposed in the following way:

$$m_{ij} = \sum_{l=1}^{\kappa} \frac{|M_{i,j}^l|}{n}$$

where each  $|M_{i,j}^l|$  represents a subset of individuals transitioning from quantile  $i$  at time  $t$  to quantile  $j$  at time  $t + 1$ . A complete partition based on the joint dynamics of the major capital and labor mobility components, is such that  $\cup_{l=1}^{\kappa} M^l = M$  and  $M^l \cap M^h = \emptyset \forall l \neq h$ . From the probabilistic perspective, this is a partition of the *same* transition probability mass into economically interpretable regions defined by the signs of component jumps, rather than a different notion of mobility.

An example of a relevant partition is one where individuals, for any given jump from percentile  $i$  to percentile  $j$  of the total income distribution (whether upward or downward), are separated into four main groups: those whose jump is characterized by a *positive* change in the distribution of capital and a *negative* change in the distribution of labor (*capital-driven mobility*); those characterized by a negative change in the distribution of capital and a positive change in the distribution of labor (*labor-driven mobility*); those whose jump is characterized by positive changes in both components (upward *homoploutic* mobility), and those whose jump is characterized by negative changes in both components (downward *homoploutic* mobility).

We can therefore decompose the matrix  $M$  as  $M = \sum_{l=1}^{\kappa} M^l$ , where each  $M^l$  represents a component of the matrix. If we define the trace of  $M$ ,  $tr(M)$ , normalized suitably, as our indicator of *relative mobility*, denoted  $\xi$ , then it can be expressed as:

$$\xi = f(tr(M)) = f\left(\sum_{l=1}^{\kappa} tr(M^l)\right),$$

where  $f$  is our normalization function. Following the approach of [Shorrocks \(1978\)](#), relative mobility  $\xi$  is defined by:

$$\xi = \frac{\left(\sum_{l=1}^{\kappa} (n_l - tr(M^l))\right)}{n}, \quad (8)$$

where  $n_l$  denotes the complete immobility of partition  $l$ .

In order to assess the contribution of different components to upward and downward mobility, in a similar vein, we can decompose the upper and lower diagonals of

$M$ , defined as  $\text{Upper}(M) = \{M_{i,j} \mid i < j\}$  and  $\text{Lower}(M) = \{M_{i,j} \mid i > j\}$ , in the following way:

$$\text{Upper}(M) = \text{Upper}\left(\sum_{l=1}^{\kappa} M^l\right), \quad \text{Lower}(M) = \text{Lower}\left(\sum_{l=1}^{\kappa} M^l\right). \quad (9)$$

In the empirical section, the contribution of each main component to the upper and lower diagonal will be suitably normalized by the total number of people in the corresponding diagonal.

### 3.3.2 Compositional and income mobility

The correlation between time 1's income,  $y_1$ , and time 2's income,  $y_2$ , can be expressed as:

$$\rho(y_1, y_2) = \frac{\text{Cov}(C_1, C_2) + \text{Cov}(C_1, L_2) + \text{Cov}(L_1, C_2) + \text{Cov}(L_1, L_2)}{\sigma_{y_1} \sigma_{y_2}}, \quad (10)$$

where  $\sigma_{y_1}$  and  $\sigma_{y_2}$  are the standard deviations of income in periods 1 and 2, respectively. This decomposition mirrors the temporal dependence structure in the probabilistic setup: own-component persistence and cross-component spillovers correspond to distinct blocks of intertemporal association, which ultimately govern how much mass concentrates on or off the transition diagonal.

Each term in the decomposition represents a distinct contribution to the overall correlation. The term  $\frac{\text{Cov}(C_1, C_2)}{\sigma_{y_1} \sigma_{y_2}}$  captures capital persistence, reflecting the stability of capital income over time, while  $\frac{\text{Cov}(L_1, L_2)}{\sigma_{y_1} \sigma_{y_2}}$  represents labor persistence, indicating the stability of labor income over time. Additionally, the terms  $\frac{\text{Cov}(C_1, L_2)}{\sigma_{y_1} \sigma_{y_2}}$  and  $\frac{\text{Cov}(L_1, C_2)}{\sigma_{y_1} \sigma_{y_2}}$  account for cross-component contributions, capturing the interdependencies between capital and labor incomes across the two periods. This straightforward decomposition can be readily incorporated into standard aggregate measures of mobility.

Following [Yitzhaki and Wodon \(2005\)](#), we can define the Gini mobility index, which measures how much individual rankings in the income distribution change between two periods, as follows:

$$G_m = \frac{G_1(1 - \Gamma_{12}) + G_2(1 - \Gamma_{21})}{G_1 + G_2} \quad (11)$$

where  $G_1$  and  $G_2$  are the total income Gini at time 1 and 2, respectively, and  $\Gamma_{12}$  and  $\Gamma_{21}$  are the directional measures of mobility, defined as follows:

$$\Gamma_{12} = \frac{\text{Cov}\left(\frac{y_1}{\mu_1}, r(y_2)\right)}{\text{Cov}\left(\frac{y_1}{\mu_1}, r(y_1)\right)}, \quad \Gamma_{21} = \frac{\text{Cov}\left(\frac{y_2}{\mu_2}, r(y_1)\right)}{\text{Cov}\left(\frac{y_2}{\mu_2}, r(y_2)\right)}.$$

In simple terms, the Gini mobility index evaluates the extent of rank movements across two income distributions. A higher  $G_m$  indicates greater mobility, meaning that individuals experience larger changes in their relative positions. Conversely, a lower  $G_m$  suggests more stability in income rankings over time.

Given equation (10), we can further decompose the covariance, for each period, as follows:

$$\text{Cov}\left(\frac{y_i}{\mu_i}, r(y_j)\right) = \text{Cov}\left(\frac{\pi_i}{\mu_i}, r(y_j)\right) + \text{Cov}\left(\frac{w_i}{\mu_i}, r(y_j)\right),$$

and by knowing that compositional inequality in terms of capital and labor (Ranaldi, 2022) and income inequality can be related by the following equation (Ranaldi and Milanovic, 2022):

$$G = \kappa \frac{I}{\alpha - \pi}, \quad (12)$$

where  $I$  is the income-factor concentration index,  $\alpha$  the contribution of capital income inequality to total income inequality,  $\pi$  the overall capital share in the economy, and  $\kappa$  an additional coefficient.<sup>11</sup> By relating equations (11), (10), and (12), we can write:

$$G_m = \frac{f(I_1, \sigma_1) \left(1 - \Gamma_{12}^\pi - \Gamma_{12}^w\right) + f(I_2, \sigma_2) \left(1 - \Gamma_{21}^\pi - \Gamma_{21}^w\right)}{f(I_1, \sigma_1) + f(I_2, \sigma_2)}, \quad (13)$$

where  $\sigma_i = \alpha_1 - \pi_i$  and  $\Gamma_{ij}^l = \frac{\text{Cov}\left(\frac{l_i}{\mu_i}, r(y_j)\right)}{\text{Cov}\left(\frac{y_i}{\mu_i}, r(y_i)\right)}$  for  $l = \pi, w$ .

From equation (13), we can compute the relative contribution of compositional inequality at time  $t$  to the Gini mobility index,  $G_m$ . Under the reasonable assumption that  $\sigma_1, \sigma_2 > 0$ , we observe that:

$$\frac{\partial G_m}{\partial I_1} > 0 \iff (1 - \Gamma_{12}^\pi - \Gamma_{12}^w) > (1 - \Gamma_{21}^\pi - \Gamma_{21}^w), \quad (14)$$

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<sup>11</sup> $\alpha = \frac{\tilde{G}_\pi \pi}{G}$  reflects the contribution of capital income inequality to overall income inequality, where  $\tilde{G}_\pi$  denotes the pseudo-Gini coefficient of capital income,  $\pi$  is the share of capital income, and  $G$  is the overall Gini coefficient.

and, similarly, we find:

$$\frac{\partial G_m}{\partial I_2} > 0 \iff (1 - \Gamma_{12}^\pi - \Gamma_{12}^w) < (1 - \Gamma_{21}^\pi - \Gamma_{21}^w). \quad (15)$$

In other words, a positive change in compositional inequality at time  $t$  positively affects the Gini mobility index, depending on the directional mobility measures, which are here considered as our measures of *compositional mobility*. If the directional mobility measure from time 1 to 2 is higher (lower) than that from time 2 to 1, then the relationship is positive (negative).

Intuitively, these results suggest that the impact of compositional inequality on mobility depends fundamentally on how income ranks are rearranged between periods. If individuals' income ranks change more significantly moving forward in time (from period 1 to 2), then greater compositional inequality initially will amplify mobility. Conversely, if rank mobility is more pronounced backward in time (from period 2 to 1), greater compositional inequality at the later time will enhance measured mobility. Thus, whether an economy benefits from increased compositional inequality — in terms of higher measured mobility — depends crucially on the temporal direction of rank changes in its capital and labor income distributions. This highlights the nuanced interplay between inequality structure and income mobility dynamics.

Another relevant observation is the relationship between the dynamics of functional income distribution, measured by the profit-to-output ratio (capital share), and income mobility. To clarify the main channels involved, we refer to equation (11), considering only its numerator for simplicity.<sup>12</sup> By applying the Lerman and Yitzhaki decomposition to the Gini coefficient at time 1 (Lerman and Yitzhaki, 1985), it can be shown that the Gini mobility index,  $G_m$ , changes in response to variations in the capital share,  $\pi$ , depending on compositional inequality and the measure of directional upward mobility,  $\Gamma_{12}$ .

Specifically, when compositional inequality is positive (i.e., capital and labor incomes are unevenly distributed across individuals), an increase in the capital share will *reduce* income mobility if compositional mobility, here measured by the second

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<sup>12</sup>Recall that the numerator of equation (11) is simply used for normalization purposes.

term in equation 16, is negative (thus implying higher persistence). This effect becomes stronger with greater compositional inequality. Formally, this relationship can be expressed as follows:<sup>13</sup>

$$\frac{\partial G_m}{\partial \pi} \approx \underbrace{I}_{\text{compositional inequality}} \times \underbrace{(1 - \Gamma_{12}^\pi - \Gamma_{12}^w)}_{\text{compositional mobility}}. \quad (16)$$

Equation (16) is useful as it links the macroeconomic dynamics of the capital share — whose rise can be associated, among other factors, with technological developments — to income mobility over time, and enrich the debate on the relationship between inequality, on the one hand, and mobility, on the other hand (Corak, 2013).

## 4 Decomposition results

In this section, we present the results from the decomposition framework outlined in subsection 3.3.1. We consider three empirical settings. In (a), we use the full sample window, defining the initial year (1993) as period 1 and the terminal year (2018) as period 2. In (b), we construct five-year windows by partitioning the 26-year observation period into five sub-periods. In (c), we adopt a year-to-year design, measuring mobility between consecutive years throughout 1993–2018. Our baseline results are obtained under setting (a); settings (b) and (c) are used as robustness analyses, with additional results available in Appendix D and upon request.

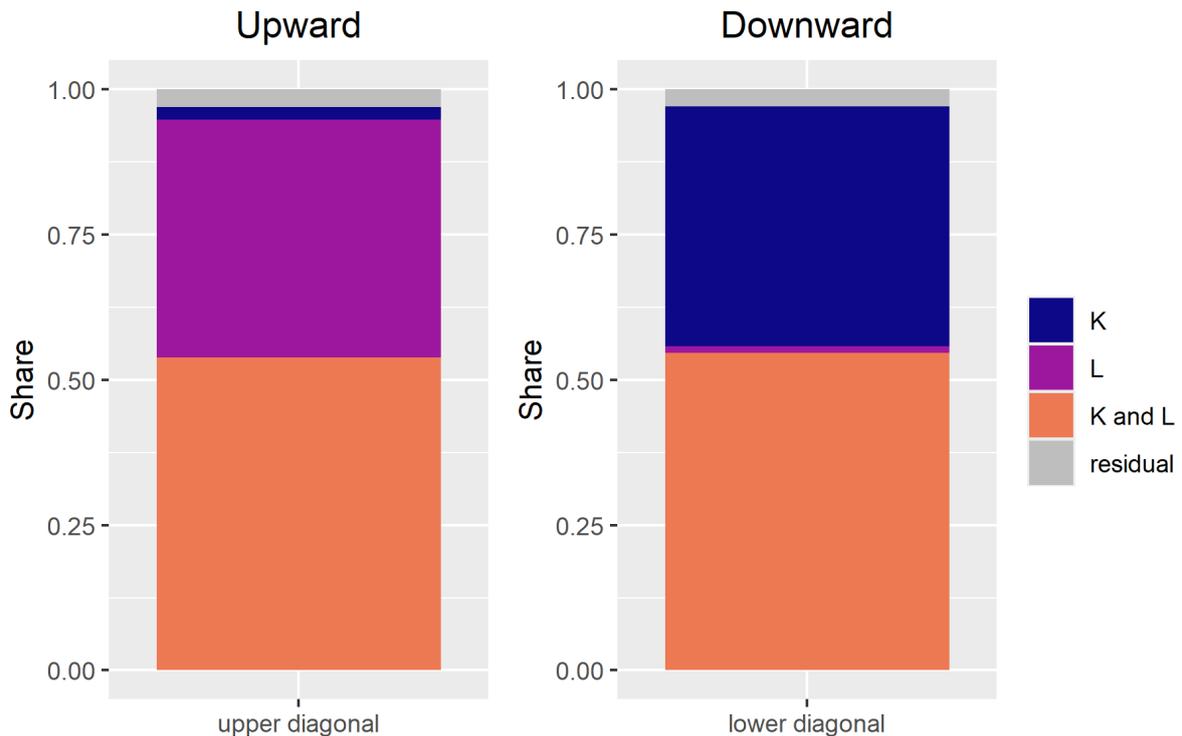
To begin, recall the transition matrix for total income (TI) shown on the left-hand side of figure 2. Focusing on upward mobility, i.e., all transitions above the main diagonal, we ask what income-component trajectories underlie these upward moves in TI. To this end, we decompose TI mobility into the factor-income contributions and report the frequencies of the dominant typologies generating relative upward mobility: (1) upward CI only (capital income rises while labor income does not), (2) upward LI only (labor income rises while capital income does not), and (3) upward

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<sup>13</sup>Equation (16) can be derived by decomposing the Gini coefficient at time 1,  $G_1$ , into the contributions of capital and labor income inequality, following Lerman and Yitzhaki’s approach, and then taking the derivative of  $G_m$  with respect to  $\pi$ , which appears as one of the components in the decomposition.

CI and LI (both components rise). We show that these three typologies account for more than 90% of all upward transitions. Analogously, for downward mobility (transitions below the main diagonal) we classify observations into (1) downward CI only; (2) downward LI only; (3) downward in CI and LI. Recall that we are focusing on unconditional transitions, hence not conditioning on individuals' positions in the total income distribution.

Figure 8: Unconditional results of decomposition of upward / downward mobility



*Note:* This figure reports the share of upward (downward) mobility attributable to changes in capital income  $K$  only, labor income  $L$  only, and the joint case in which both components move upward (downward) simultaneously. Recall that these results apply to the (a) setting, in which we use the full sample window, defining the initial year (1993) as period 1 and the terminal year (2018) as period 2. The gray area represents the residual.

In the left panel of figure 8, we observe that upward mobility is driven by either increases in both CI and LI (orange area, about 54% of the total) or by increases in LI with non-increasing CI (purple area, about 41% of the total). Negligible shares for upward CI only conveys that this typology is not a significant determinant of up-

ward mobility. Although the contributions vary slightly over time, no clear temporal pattern is discernible (see Appendix D for evidence of this result in the (b) five-year windows and (c) year-to-year settings).

Turning to downward mobility (right panel of Figure 8), more than half of all downward transitions are accounted for by cases in which both CI and LI are non-increasing (i.e., stagnant or declining) simultaneously. The second dominant typology consists of downward movements in CI only. By contrast, transitions driven solely by declines in LI represent a negligible share.

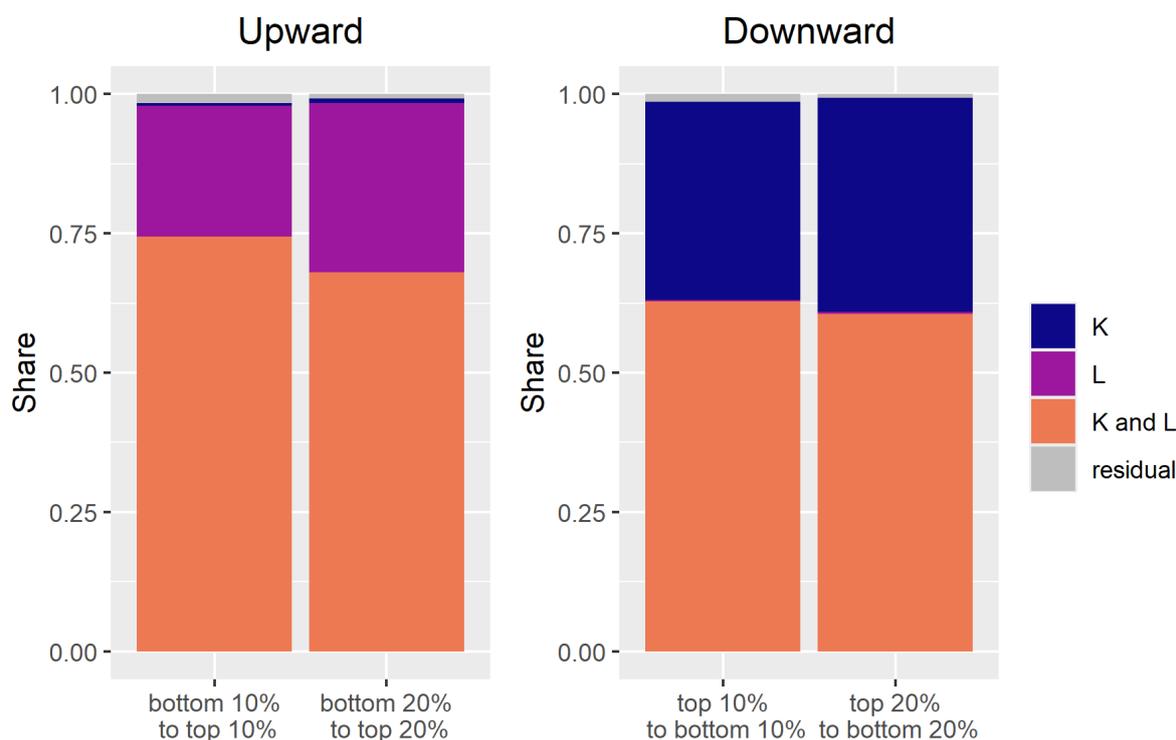
Overall, the decomposition in Figure 8 reveals a clear asymmetry: labor income (LI) accounts for a larger share of upward mobility, whereas capital income (CI) contributes more prominently to downward mobility.

#### 4.1 Conditioning on jump size

In the next step, we investigate whether the above pattern is robust to conditioning on large upward or downward jumps. We focus on jumps from the bottom 10% (20%) to the top 10% (20%) of the total income distribution, and viceversa (top to bottom) for downward movements.

Focusing on upward movements (the left panel in figure 9), we observe that the joint dynamics of CI and LI becomes more predominant than in the unconditional case. In other words, the importance of positive changes in both CI and LI to explain movements from the very bottom to the very top increases as we tighten the definition of the far bottom and top. More interestingly, the conditional decomposition corroborates the baseline pattern in Figure 8. Comparing the LI and CI upward typologies, we confirm that upward mobility is driven primarily by increases in labor income (LI). By contrast, transitions characterized by increases in CI only account for a negligible share, regardless of whether we condition on the bottom (top) 10% or 20% of the distribution.

Figure 9: Conditional results of decomposition of upward / downward mobility



*Note:* The graph displays the share of upward (downward) mobility explained solely by upward (downward) movement in capital income (K), only upward (downward) movement in labor income (L), and upward (downward) movement in both income components (K and L), conditioned on moving from the bottom (top) 10% to the top (bottom) 10%, or from the bottom (top) 20% to the top (bottom) 20%, respectively.

Focusing on downward movements (the right panel in figure 9), we observe that the joint dynamics of CI and LI becomes once again more predominant than in the unconditional case. We confirm also for downward movements that mobility is driven primarily by increases in CI, as shown in figure 8. By contrast, transitions characterized by drops in LI only account for a negligible share, regardless of whether we condition on the bottom (top) 10% or 20% of the distribution.

## 4.2 Investigating joint capital-labor dynamics

The unconditional and conditional decompositions indicate that joint capital–labor income dynamics are an important determinant of both upward and downward mo-

bility, as shown in Figures 8 and 9. Focusing on upward mobility, it is possible that the category of joint capital–labor movements masks a substantially larger contribution of CI relative to LI. If so, this would disqualify our earlier finding that LI is the primary driver of upward mobility. We therefore examine the joint upward and downward capital–labor dynamics in greater detail. To begin with, we investigate closer joint upward mobility, by producing a set of summary statistics presented in Table 3. A set of figures on jump size related to joint upward mobility is available in the Appendix under D.2.

Table 3: Joint upward mobility - Summary stats

metric	value
mean \$ labor jump	38370.92
mean \$ capital jump	9247.69
median \$ labor jump	30860.27
median \$ capital jump	308.48
mean percentile labor jump	27.77
mean percentile capital jump	30.80
mean share of labor jump	0.90
median share of labor jump	0.99
share individuals w. labor jump > capital jump	0.93

*Note:* This table presents summary statistics for the third component of the partition, namely the category for which we observe joint upward mobility from capital and labor incomes. Notice that we focus exclusively on the unconditional results.

On average, individuals in this category experience an increase of approximately \$38,300 in labor income and \$9,200 in capital income. The median increase in labor income (\$30,800) is about two orders of magnitude larger than the median increase in capital income (\$308), indicating that the typical upward move within this group is driven primarily by labor income. Consistent with this interpretation, for 93% of individuals in the category the increase in labor income exceeds the increase in capital income. At the same time, expressed in terms of movements across percentiles within the respective univariate distributions, capital-income gains are slightly larger. Thus, although these individuals move at least as far within the capital-income distribution as within the labor-income distribution, the absolute increase in labor income in

USD far exceeds the corresponding increase in capital income. These results do not contradict the main findings for upward mobility reported in the unconditional and conditional analyses.

Let us now turn to the analysis of joint downward total income jumps, reported in Table 4.

Table 4: Joint downward mobility - Summary stats

Metric	Value
mean \$ labor jump	-143,936.67
mean \$ capital jump	-490,819.28
median \$ labor jump	-27,852.63
median \$ capital jump	-384.52
mean percentile labor jump	-27.27
mean percentile capital jump	-27.01
mean share of labor jump	0.89
median share of labor jump	0.99
share individuals w. $\text{abs}(\text{labor jump}) > \text{abs}(\text{capital jump})$	0.92

*Note:* This table presents summary statistics for the third component of the partition, namely the category for which we observe joint downward mobility for both capital and labor incomes. Notice that we focus exclusively on the unconditional results.

The difference in magnitude relative to joint upward jumps is substantial: mean CI declines are approximately 55 times larger than mean CI increases, as shown in table 3. Similarly, average labor income decreases exceed average labor income increases, though by a smaller factor of about 4. On average, we observe negative capital income jumps of roughly 490,800 USD, while labor income jumps amount to approximately 143,900 USD. However, the median values of capital and labor income jumps suggest a much smaller difference between upward and downward movements. This discrepancy highlights the significant influence of extreme observations, particularly pronounced in large downward shifts in capital income.

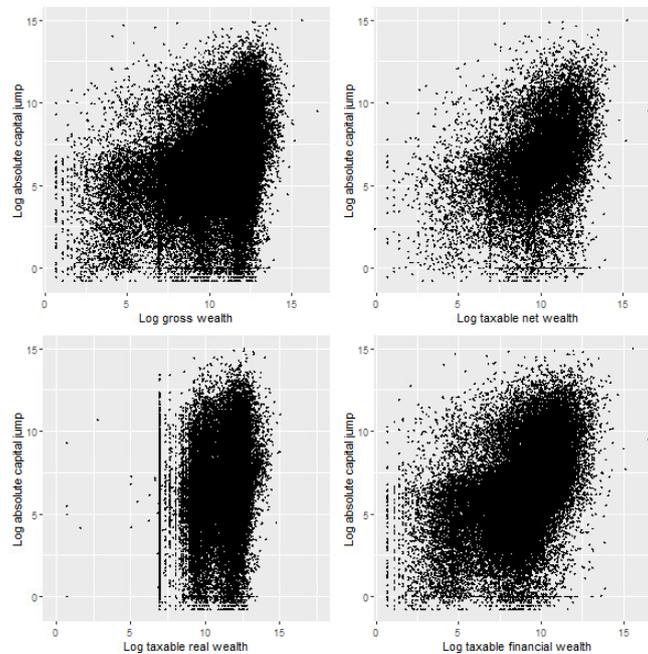
The last row of Table 4 indicates that downward labor jumps are far more common, accounting for a remarkable 92% of all joint downward mobility cases. Capital jumps are, however, larger on average (490 800 USD), but they are concentrated among a limited subset of individuals. Thus, while an important part of downward total income mobility is driven by downward capital income mobility alone, the neg-

ative jumps in labor income are relatively more important for individuals who experience downward movement in both income factors.

#### 4.2.1 Type of assets and joint upward mobility

A further informative exercise for the subsample experiencing joint upward mobility is to examine the relationship between their increases in capital income and the composition of their asset holdings in the initial year (1993). In particular, we ask whether upward capital-income jumps are more strongly associated with initial holdings of real assets (e.g., housing and other non-financial wealth) or with initial holdings of financial assets.

Figure 10: Capital income upward jumps and wealth



*Note:* The graph displays four different scatterplots. The Y axis displays the log of the absolute jump in CI, while the X axis displays log of gross wealth (upper left), log of net wealth (upper right), log of real capital (down left), and log of financial capital (down right).

Figure 10 plots scatter diagrams with the log of the absolute change in CI over 1993–2018 on the vertical axis and, on the horizontal axis, the log of (i) gross wealth (upper-left panel), (ii) net wealth (upper-right panel), (iii) real assets (lower-left panel), and (iv) financial assets (lower-right panel), each measured in 1993. The correla-

tion between the log absolute change in capital income and initial financial wealth is substantially stronger ( $r = 0.44$ ) than the corresponding correlation with initial real wealth ( $r = 0.20$ ). This pattern suggests that gross financial assets in 1993 are more closely associated with subsequent upward jumps in capital income than are real assets.

However, it is important to note that the direct mechanism, i.e., initial financial capital allowing for more capital accumulation and thus more capital income, is just one among many. High initial wealth could also be associated with certain parental characteristics, such as professional networks, which in turn provide better access to higher-paying jobs and thereby facilitate greater capital accumulation out of labor income allowing for more capital income in the future. While this is not the central focus of the present work, it could open up many interesting avenues for future research on this matter.

## 5 Robustness analysis

In this section, we test robustness of the main results with respect to the income definition, and cohort selection.

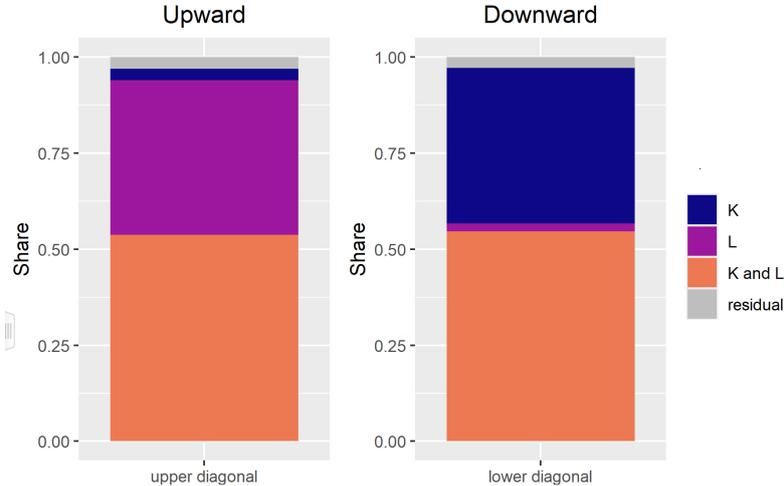
### 5.1 Allocating self-employment income

In the baseline setting, we treat self employment income as entirely attributable to labor. This is a restrictive assumption, but it delivers a well-defined benchmark. In the following, we relax this restriction and examine the robustness of the main results to an alternative allocation.

A decomposition of self-employment income is further motivated by evidence suggesting that self-employed individuals may exhibit different mobility patterns compared to those who rely primarily on wage income. Notably, prior studies have found that the self-employed tend to experience greater upward mobility than wage earners ([Lindquist and Vladasel, 2025](#), [Quadrini, 2000](#)). A more realistic treatment involves decomposing self-employment income into labor and capital components,

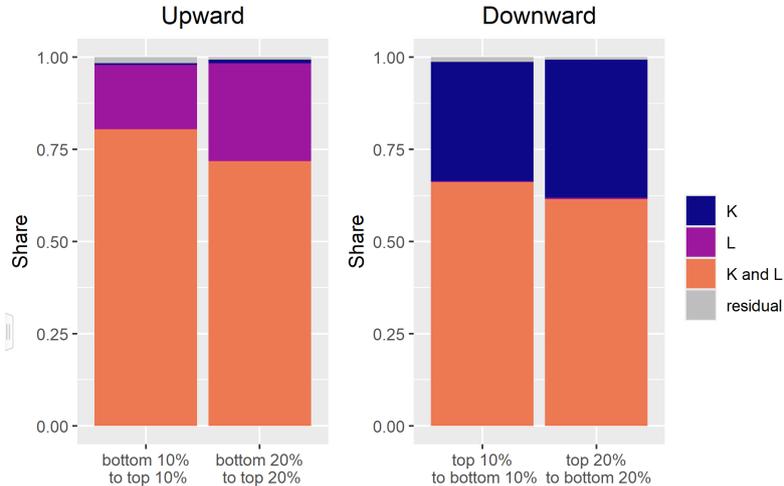
assigning one-third to capital income and the remaining two-thirds to labor income (Glyn, 2011). We perform this decomposition and show in Figure 11 the results for the unconditional setting, while Figure 12 presents the conditional results.

Figure 11: Unconditional results of decomposition - SE income split



Note: The graph displays the share of upward (downward) mobility explained solely by upward (downward) movement in capital income (K), only upward (downward) movement in labor income (L), and upward (downward) movement in both income components (K and L).

Figure 12: Conditional results of decomposition - SE income split



Note: The graph displays the share of upward (downward) mobility explained solely by upward (downward) movement in capital income (K), only upward (downward) movement in labor income (L), and upward (downward) movement in both income components (K and L), conditioned on moving from the bottom (top) 10% to the top (bottom) 10%, or from the bottom (top) 20% to the top (bottom) 20%, respectively.

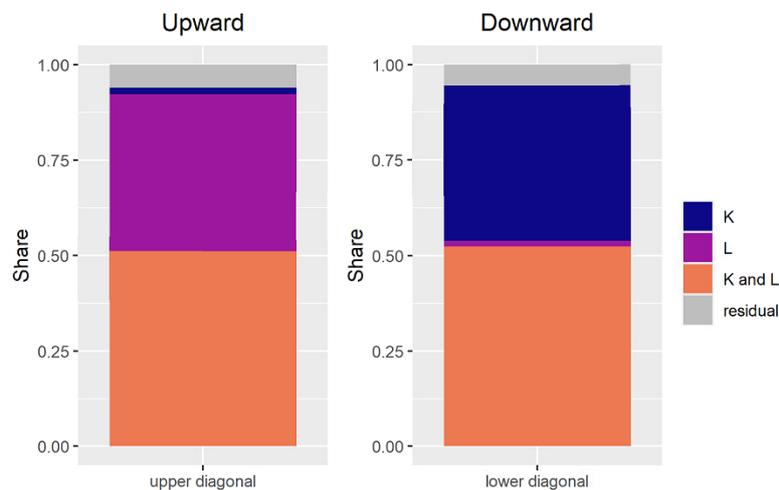
The patterns in figures 11 and 12 are largely indistinguishable from those in the baseline sample without the self-employment income split (figures 8 and 9).

Focusing on the discrepancy with the baseline setting, allocating a portion of the self-employment income to capital income leads to a slightly higher share of the joint upward mobility component, especially when conditioning on jumps from bottom to top of the distribution (figure 12).

## 5.2 Cohort selection

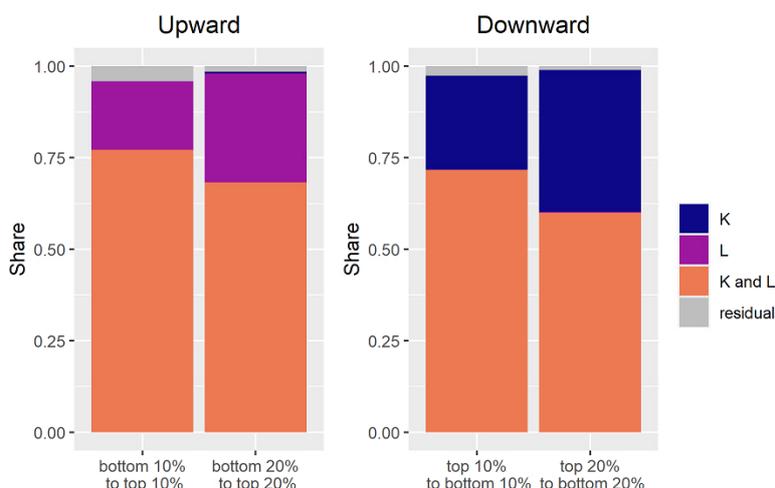
The baseline results may be sensitive to the chosen cohort definition. As a robustness check, we re-estimate the analysis on an alternative cohort to assess whether the findings are preserved. This time, we focus on individuals born between 1955 and 1959 and again follow their income trajectories over the full observed life cycle. This cohort is aged 34–38 in 1993 and reaches ages 59–63 by 2018. Figures 13 and 14 report the corresponding unconditional and conditional results. The patterns are qualitatively similar to those obtained in the baseline cohort, indicating that the main conclusions are not driven by the particular cohort definition and are therefore robust to cohort selection.

Figure 13: Unconditional results of decomposition - Robustness cohort selection



*Note:* The graph displays the share of upward (downward) mobility explained solely by upward (downward) movement in capital income (K), only upward (downward) movement in labor income (L), and upward (downward) movement in both income components (K and L).

Figure 14: Conditional results of decomposition - Robustness cohort selection



*Note:* The graph displays the share of upward (downward) mobility explained solely by upward (downward) movement in capital income (K), only upward (downward) movement in labor income (L), and upward (downward) movement in both income components (K and L), conditioned on moving from the bottom (top) 10% to the top (bottom) 10%, or from the bottom (top) 20% to the top (bottom) 20%, respectively.

## 6 Concluding remarks

Do individuals move up (or down) the ladder due to jumps in capital or labor income, or both? In other words, shall individuals invest in human capital and try to climb the ladder through remuneration for their labour, or does it pay more off to accumulate financial wealth in order to boost capital incomes? The literature on relative income mobility has so far mostly focused on aggregate welfare measures such as total income, or simply on earnings due to data availability considerations. However, little attention has been paid to the sources of total income mobility by focusing on its two principal components: capital and labor income. Taking a life-cycle perspective and exploiting register data from Norway covering 293,875 individuals across 26 years, this paper studies relative capital and labor income mobility, and decomposes total income mobility into its constituent factors.

To this end, this paper introduces a novel mobility decomposition framework based on the decomposition of inter-temporal income jumps, suitable for life-cycle analysis. We report several results on this topic. *First*, while labor income mobility

along its unidimensional distribution tends to be larger than capital income mobility, different relative mobility indicators produce different mobility rankings. This result further justifies the need to understand what contributes to upward and downward relative mobility through the decomposition framework.

We report that while the interaction of both factors is key to determining both upward and downward total income mobility dynamics, labor income alone explains upward total income mobility more than capital income does, and vice versa: capital income alone is a key determinant of downward income mobility patterns. These results have been discussed in light of the recent stream of research on compositional inequality and homoploutia, focusing on the study of the joint distribution of capital and labor income across individuals, both theoretically and empirically.

This comparison has confirmed the role of both factors in determining one's income status, as described by the recent trends in homoploutia in the US ([Berman and Milanovic, 2024](#)). Moreover, labor income appears to be the main determinant of total income mobility, as shown in recent global inequality studies on capital and labor ([Ranaldi, 2025](#)). However, our results also indicate that these findings are mitigated when considering large jumps along the distribution.

To conclude, we see this paper as the first attempt at linking studies on the functional income distribution with mobility studies. We therefore encourage further research on this subject from other countries, in order to obtain a coherent picture of stylized facts on the role of factor incomes and social mobility.

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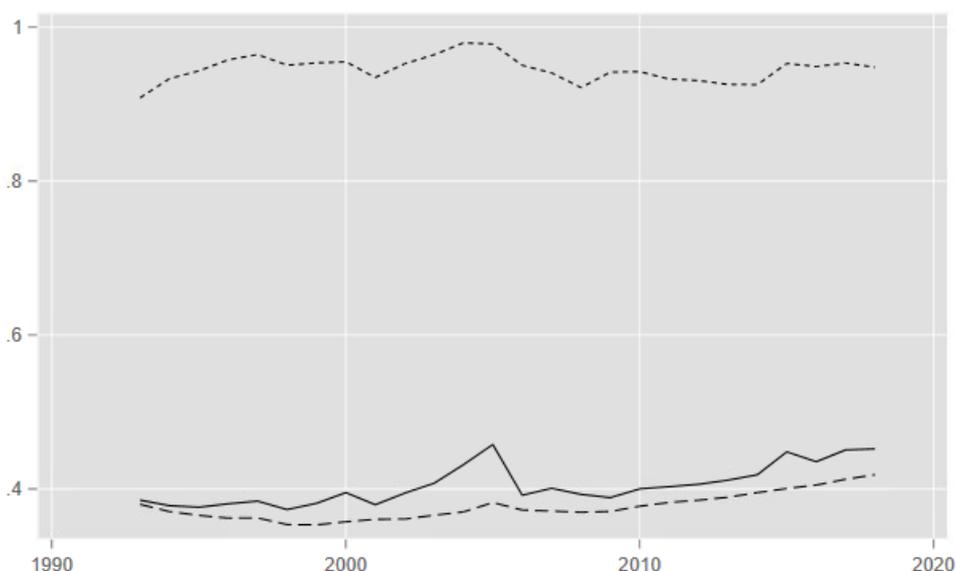
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# Appendices

## A Inequality statistics

Inequality and exchange mobility are closely interconnected. Ideally, to study mobility dynamics independently of inequality, the dispersion of factor incomes (and consequently total income) would need to remain constant over time. However, we acknowledge that this is often not the case. Even when the Gini coefficient for total income remains stable, opposing contributions from capital and labor income may be at play. To illustrate these dynamics, Figure 15 presents the sample Gini coefficients for Capital Income (CI), Labor Income (LI), and Total Income (TI) over the entire period.

Figure 15: Time series of Gini 1993 – 2018 - TI, CI, LI



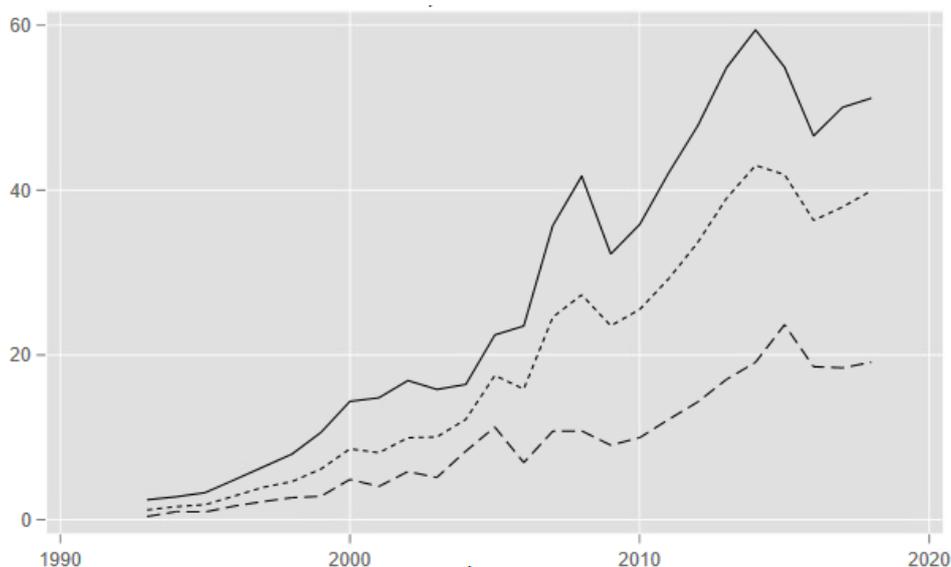
Note: This graph presents the sample time series of Gini coefficients for capital income (short-dashed line), labor income (dashed line), and total income (solid line) over the period 1993-2018.

Figure 15 shows that the Gini coefficient for capital income (short-dashed line) increased from 0.91 in 1993 to 0.98 in 2005, driven by a surge in dividend payments to shareholders ahead of anticipated tax regime changes in 2006 (Iacono and Palagi, 2022). Since then, the CI Gini has remained relatively stable, fluctuating between 0.94 and 0.95. The Gini coefficient for labor income (dashed line) has ranged between 0.35

and 0.41, exhibiting a slow but steady increase since the early 2000s. Meanwhile, the total income Gini initially rose due to the growing concentration of capital income at the top, peaking in 2005. It then declined until 2009 before resuming a gradual upward trend, paralleling the LI Gini, and reaching 0.45 in 2018.

Let us now move to the dynamics of the joint distribution of capital and labor income through two key concepts and indicators: *homoploutia* and *compositional inequality*. *Homoploutia* refers to the phenomenon in which the same individuals rank among the top earners in both capital and labor income distributions, as documented for the U.S. by [Berman and Milanovic \(2024\)](#). While [Berman and Milanovic \(2024\)](#) estimate homoploutia cross-sectionally, this study examines the extent to which individuals within a cohort persistently cluster in the top shares of both distributions over time. In other words, we analyze the dynamics of homoploutia *across* the life cycle.

Figure 16: The degree of homoploutia 1993 – 2018



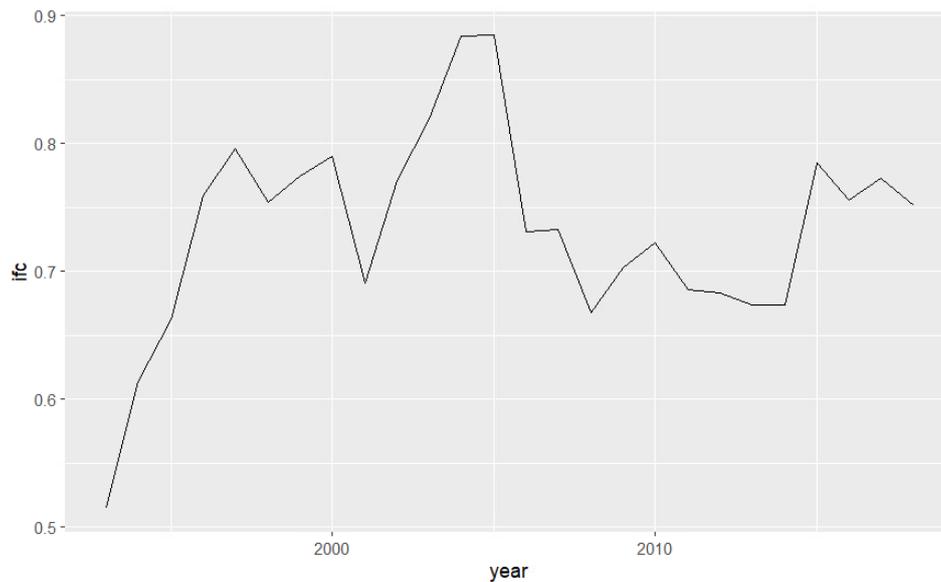
*Note:* This graph shows the degree of homoploutia ([Berman and Milanovic, 2024](#)) within the top decile of the capital and labor income distributions (solid line), within the top 5% of both distributions (short dash), and within the top 1% (dashed), over the period 1993–2018. Homoploutia measures the share of individuals who are simultaneously at the top of both the labor and capital income distributions.

To capture this, we employ three distinct measures of homoploutia, illustrated in Figure 16: (1) the share of individuals in the top 10% of both distributions, (2) the

share of individuals in the top 5% of both distributions, and (3) the share of individuals in the top 1% of both distributions. Results show that homoploutia has been consistently increasing over the life cycle, with a steeper rise for the top 10% and a more moderate increase for the top 1%. This finding suggests that the share of individuals within a cohort who occupy the top ranks of both the capital and labor income distributions has been rising in Norway. This trend goes in the same direction as the recent work by [Berman and Milanovic \(2024\)](#), which reports a positive pattern for the US using cross-sectional data. That said, the level shown for the US is about half of the value we find for Norway when we adopt a life-cycle perspective. Our result therefore enriches this debate by showing that cross-sectional evidence can conceal important heterogeneity across the life cycle, ranging from less than 5% of individuals occupying the top 10% of both distributions to about 60% at the end of the life cycle. This pattern is explained by the role of capital accumulation over the life course, partly driven by a lifetime of savings transformed into capital income, as well as private pension plans.

When examining the dynamics of capital and labor income composition across the income distribution (Figure 17) — referred to as compositional inequality — we observe a slightly different pattern. While compositional inequality increased significantly before the 2000s, it has since exhibited notable fluctuations. However, the overall trend has stabilized around a level of 0.75 in the IFC index, our preferred measure of compositional inequality.

Figure 17: IFC Index 1993 – 2018



*Note:* This graph shows the Income-Factor Concentration (IFC) Index (Ranaldi, 2022) over the period 1993–2018. The IFC Index ranges between +1 and –1. It equals +1 when capital income is concentrated at the top of the total income distribution and labor income at the bottom. It equals 0 when both income sources are distributed proportionally across the total income ranking. Finally, it equals –1 when labor income is concentrated at the top and capital income at the bottom of the total income distribution.

When considered together, Figures 16 and 17 indicate that, over the life cycle, there is an increasing share of individuals benefiting from multiple sources of income at the top. However, when examining the entire distribution, Norway remains a country characterized by a stark separation between income-rich capital earners and income-poor laborers. This result aligns with recent findings by Ranaldi and Milanovic (2022), which show that Scandinavian countries are exceptional in combining very low income inequality with high compositional inequality relative to other countries worldwide. Ranaldi and Milanovic (2022) argue that this pattern is driven by a compressed wage distribution alongside extreme wealth concentration. Moreover, our findings on the dynamics of compositional inequality across the life-cycle align well with those of Iacono and Palagi (2022), who document that compositional inequality in Norway has been declining since 2005, despite remaining at a high absolute level.

## B Probabilistic Setup

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space. In each period  $t$ , individual income is composed of two *nonnegative* random variables: capital income  $\Pi_t \geq 0$  and labor income  $W_t \geq 0$ . Total income is their sum,  $Y_t = \Pi_t + W_t$ . We denote the marginal cumulative distribution functions (cdf's) by  $F_{\Pi,t}(x) = \mathbb{P}(\Pi_t \leq x)$ ,  $F_{W,t}(x) = \mathbb{P}(W_t \leq x)$ ,  $F_{Y,t}(x) = \mathbb{P}(Y_t \leq x)$ , and recall the associated quantile functions (generalized inverses)  $Q_{\Pi,t}(p) = \inf\{x \in \mathbb{R}_+ : F_{\Pi,t}(x) \geq p\}$ ,  $Q_{W,t}(p) = \inf\{x \in \mathbb{R}_+ : F_{W,t}(x) \geq p\}$ ,  $Q_{Y,t}(p) = \inf\{x \in \mathbb{R}_+ : F_{Y,t}(x) \geq p\}$ ,  $p \in (0, 1)$ .

A central device in what follows is the transformation of *income levels* into *ranks*. The intuition is that, while levels depend on units and scales, ranks are scale-free: they map each observation into a number in  $[0, 1]$  interpretable as a population position (a *cumulative share*). Formally, define the probability integral transforms  $U_{\Pi,t} = F_{\Pi,t}(\Pi_t)$ ,  $U_{W,t} = F_{W,t}(W_t)$ , so that  $(U_{\Pi,t}, U_{W,t}) \in [0, 1]^2$  has uniform marginals. Expressing variables in rank space each marginal standard uniform on  $[0, 1]$  by construction; any remaining structure in their joint behavior therefore reflects only how ranks comove, that is, the dependence pattern, independently of the shapes or scales of the original distributions. The transformation is essentially lossless because it can be inverted through the quantile functions: given the rank, one recovers the associated income level via  $\Pi_t = Q_{\Pi,t}(U_{\Pi,t})$  and  $W_t = Q_{W,t}(U_{W,t})$ . Hence no information about individual positions in the distribution is discarded. This change of variables anticipates the empirical strategy of the paper: once outcomes are expressed in rank space, mobility statistics can be read as statements about how probability mass moves *across* positions.

The joint distribution of  $(\Pi_t, W_t)$  is characterized by a *within-period* copula  $C_t$ :

$$\mathbb{P}(\Pi_t \leq x, W_t \leq w) = C_t(F_{\Pi,t}(x), F_{W,t}(w)).$$

The copula summarizes contemporaneous alignment between capital and labor income ranks; its feasible range is bounded by the Fréchet–Hoeffding envelopes (see, e.g., [Nelsen \(2006\)](#), for a discussion). These bounds are the natural benchmarks for the

alignment component used in our decomposition; see Appendix C for the application to the alignment coefficient. The copula takes as inputs the marginal ranks  $F_{\Pi,t}(x)$  and  $F_{W,t}(w)$ , which are uniformly distributed by construction. Hence the copula operates in rank space and captures exclusively how positions in the two marginal distributions are associated.

Relative mobility concerns how rank vectors evolve over time. We model the transition  $(U_{\Pi,t}, U_{W,t}) \rightarrow (U_{\Pi,t+1}, U_{W,t+1})$  via a temporal (equivalently, *conditional*) copula  $C_t$  that specifies the conditional distribution of next-period ranks given current ranks:<sup>14</sup>

$$\mathbb{P}(U_{\Pi,t+1} \leq u', U_{W,t+1} \leq v' \mid U_{\Pi,t} = u, U_{W,t} = v) = C_t(u', v' \mid u, v), \quad (u, v, u', v') \in [0, 1]^4.$$

This object captures persistence, reranking, and cross-component transmission while leaving marginal distributions free to change over time. In this way, the model isolates the sole object that drives reranking: *conditional dependence in ranks*. Given  $(U_{\Pi,t+1}, U_{W,t+1})$ , income levels follow from  $\Pi_{t+1} = Q_{\Pi,t+1}(U_{\Pi,t+1})$ ,  $W_{t+1} = Q_{W,t+1}(U_{W,t+1})$ , and therefore  $Y_{t+1} = \Pi_{t+1} + W_{t+1}$ . These probabilistic objects provide the backbone of the empirical design developed later: observed transitions across income positions are interpreted as realizations of the rank dynamics governed by  $C_t$ , while changes in levels follow from the quantile mappings. The transition matrices computed in the empirical section are therefore sample analogues of probabilities implied by this copula.

Within this rank-based environment, define an individual's baseline total-income rank at time  $t$  as the random variable  $p_{i,t} := F_{Y,t}(Y_{i,t})$ . The total income jump is the deviation of realized next-period income from the counterfactual income at the same baseline rank, as modeled in the main body of the paper:

$$\epsilon_i := Y_{i,t+1} - Q_{Y,t+1}(p_{i,t}).$$

Although dependence is modeled in rank space, mobility outcomes are evaluated in levels through the quantile mappings. Consequently, realized movements in total

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<sup>14</sup>The study of temporal copulas is the analogue of the study of *temporal dependence* (see [Cherubini et al. \(2016\)](#)).

income are ultimately governed by dollar changes  $\epsilon_i$ , rather than by the number of percentiles crossed within a component distribution. Component-specific jumps are defined using component baseline ranks:

$$\epsilon_{\pi,i} := \Pi_{i,t+1} - Q_{\Pi,t+1}(F_{\Pi,t}(\Pi_{i,t})), \quad \epsilon_{w,i} := W_{i,t+1} - Q_{W,t+1}(F_{W,t}(W_{i,t})).$$

Since total ranks generally differ from component ranks, the total jump decomposes as follows:

$$\epsilon_i = \epsilon_{\pi,i} + \epsilon_{w,i} + B_i, \tag{17}$$

$$B_i := -Q_{Y,t+1}(F_{Y,t}(Y_{i,t})) + Q_{\Pi,t+1}(F_{\Pi,t}(\Pi_{i,t})) + Q_{W,t+1}(F_{W,t}(W_{i,t})). \tag{18}$$

The residual  $B_i$  is induced by the dependence structure encoded by  $(C_t, C_t)$  and measures how component ranks map into total-income ranks (see Appendix C for further analytical discussion about the alignment coefficient and its dependence structure).

To connect individual-level shocks to the distributional implications implied by the model, we summarize mobility along the baseline rank. For  $p \in (0, 1)$ , define conditional profiles  $m_Y(p) = \mathbb{E}[\epsilon_i \mid p_{i,t} = p]$ ,  $m_{\Pi}(p) = \mathbb{E}[\epsilon_{\pi,i} \mid p_{i,t} = p]$ ,  $m_W(p) = \mathbb{E}[\epsilon_{w,i} \mid p_{i,t} = p]$ ,  $m_B(p) = \mathbb{E}[B_i \mid p_{i,t} = p]$ , which describe how mobility and its sources vary with initial rank. These objects can be interpreted as the rank-continuous counterparts of the entries of the transition matrix for total income, which are later decomposed into the jumps of each component, as introduced in the main body of the text in Equation 7. Studying these profiles is equivalent to studying how the temporal copula redistributes probability mass conditional on the origin rank.

This representation makes clear that understanding mobility requires specifying how ranks are jointly redistributed across periods. In other words, once individual outcomes are mapped into rank space, the key remaining ingredient is the temporal dependence structure governing their evolution. We therefore turn to a parametric description of this object.

## B.1 Parametric temporal copulae for rank dynamics

Once dependence is parameterized, empirical counterparts of mobility statistics can be mapped back to a small set of interpretable parameters. The previous section leaves  $C_t$  unspecified. To obtain sharp interpretation and tractable expressions, we now impose a parametric structure on rank dynamics, while maintaining the rank-based separation between marginals and dependence. The goal is not to restrict the definition of mobility, but to obtain a low-dimensional representation that can be estimated and used for comparative statics. In empirical applications, ranks are approximated by pseudo-observations; the theoretical objects below remain valid if  $\hat{F}$  is replaced by  $F$ . Given data  $\{(\pi_{i,t}, w_{i,t}, \pi_{i,t+1}, w_{i,t+1})\}_{i=1}^n$ , define pseudo-observations:

$$\hat{U}_{\Pi,t,i} = \hat{F}_{\Pi,t}(\pi_{i,t}), \quad \hat{U}_{W,t,i} = \hat{F}_{W,t}(w_{i,t}), \quad \hat{U}_{\Pi,t+1,i} = \hat{F}_{\Pi,t+1}(\pi_{i,t+1}), \quad \hat{U}_{W,t+1,i} = \hat{F}_{W,t+1}(w_{i,t+1}),$$

where  $\hat{F}$  denotes the empirical cdf. These transforms isolate dependence from marginal dynamics and allow us to model  $C_t$  directly in rank space. We adopt a Gaussian temporal copula (see, e.g., [Durante and Sempi \(2015\)](#)) as a baseline because it yields an explicit conditional law and interpretable parameters. The Gaussian assumption should be viewed as a tractable laboratory: it converts qualitative dependence statements into computable transition probabilities.

Let  $\mathbf{U}_i = (\hat{U}_{\Pi,t,i}, \hat{U}_{W,t,i}, \hat{U}_{\Pi,t+1,i}, \hat{U}_{W,t+1,i}) \in (0, 1)^4$ ,  $\mathbf{Z}_i = \Phi^{-1}(\mathbf{U}_i)$ , where  $\Phi^{-1}$  is applied componentwise. Assume  $\mathbf{Z}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$ .<sup>15</sup> The matrix  $\mathbf{R}$  is partitioned as

$$\mathbf{R} = \begin{pmatrix} \mathbf{R}_{tt} & \mathbf{R}_{t,t+1} \\ \mathbf{R}_{t+1,t} & \mathbf{R}_{t+1,t+1} \end{pmatrix}, \quad \mathbf{R}_{tt}, \mathbf{R}_{t+1,t+1} \in \mathbb{R}^{2 \times 2}.$$

Intuitively,  $\mathbf{R}_{tt}$  and  $\mathbf{R}_{t+1,t+1}$  describe contemporaneous alignment between capital and labor ranks within each period, whereas the off-diagonal blocks  $\mathbf{R}_{t,t+1}$  and  $\mathbf{R}_{t+1,t}$  describe how today's positions are connected to tomorrow's ones. Here  $\mathbf{R}_{tt}$  governs within-period alignment at time  $t$  (analogous to  $C_t$ ), while

$$\mathbf{R}_{t,t+1} = \begin{pmatrix} \rho_{\Pi\Pi} & \rho_{\Pi W} \\ \rho_{W\Pi} & \rho_{WW} \end{pmatrix}$$

<sup>15</sup>The zero mean is without loss of generality: after the probability integral transform, location shifts carry no economic content, and dependence is entirely summarized by the correlation matrix.

encodes intertemporal rank dependence. In particular,  $\rho_{\text{III}}$  and  $\rho_{WW}$  capture persistence in capital and labor ranks, whereas  $\rho_{\text{IW}}$  and  $\rho_{\text{WI}}$  capture cross-component spillovers across time. Formally, each entry is a correlation between latent Gaussian rank scores; for instance  $\rho_{\text{III}} = \text{Corr}(Z_{\text{I},t}, Z_{\text{I},t+1})$ , and similarly for the other elements of the block. High own-component persistence reduces the probability that the component rank leaves its current neighborhood, e.g. that the binned rank changes,  $R_{\text{I},t+1} \neq R_{\text{I},t}$  or  $R_{W,t+1} \neq R_{W,t}$  for a fixed partition of  $[0, 1]$ , thereby lowering the incidence of capital- or labor-driven reranking. Conversely, lower persistence or stronger cross-effects increase the likelihood that at least one component changes position, raising the probability of component-driven or joint (homoploutic) mobility events.

Under this specification, the conditional distribution of next-period latent ranks is Gaussian:

$$\mathbf{Z}_{t+1} \mid \mathbf{Z}_t \sim \mathcal{N}(\mathbf{R}_{t+1,t} \mathbf{R}_{tt}^{-1} \mathbf{Z}_t, \mathbf{R}_{t+1,t+1} - \mathbf{R}_{t+1,t} \mathbf{R}_{tt}^{-1} \mathbf{R}_{t,t+1}),$$

where  $\mathbf{Z}_t = (Z_{\text{I},t}, Z_{W,t})'$  and  $\mathbf{Z}_{t+1} = (Z_{\text{I},t+1}, Z_{W,t+1})'$ . This expression follows from standard properties of the multivariate normal distribution: once current ranks are observed, the best linear predictor of future ranks is proportional to them, with uncertainty given by the remaining unexplained covariance. This provides an operational rank-transition mechanism consistent with the temporal copula  $C_t$ . Because this law determines how probability mass moves across rank configurations from  $t$  to  $t + 1$ , it is the key input for any aggregate mobility statistic derived from the model. Once this mechanism is specified, aggregate mobility indices become deterministic functions of the dependence parameters.

## B.2 Mobility as a functional of dependence

We now connect the probabilistic primitives to aggregate mobility measures. Once marginals are fixed — meaning that the cross-sectional distributions of capital and labor incomes at each date are taken as given — rank-based mobility statistics depend entirely on the dependence structure (within and across time), i.e. on  $(C_t, C_t)$ . This viewpoint makes explicit that empirical mobility indices summarize how probability

mass is redistributed across rank transitions. The empirical analysis can thus be interpreted as measuring features of this redistribution.

Fix a partition of  $[0, 1]$  into  $K$  rank bins and let  $R_{Y,t}$  denote the bin containing  $F_{Y,t}(Y_t)$ . The transition matrix  $M$  has entries  $m_{ij} = \mathbb{P}(R_{Y,t} = i, R_{Y,t+1} = j)$ , in line with Equation 7. Since total ranks are functions of component ranks, each  $m_{ij}$  can be written as an integral of the temporal copula density over the subset of rank realizations producing a move from bin  $i$  to bin  $j$ :

$$m_{ij} = \int_{\mathcal{A}_{ij}} c_{C_t}(\mathbf{u}) d\mathbf{u},$$

where  $\mathbf{u} = (u_{\Pi,t}, u_{W,t}, u_{\Pi,t+1}, u_{W,t+1})$  denotes a generic realization of the rank vector in  $[0, 1]^4$ , and  $\mathcal{A}_{ij}$  is the corresponding region of realizations that map into the origin-destination event. Hence the transition matrix, its trace, upward and downward mobility, and any partition  $M = \sum_l M^l$  are all functionals of  $C_t$  (and of  $C_t$  through the mapping from components to totals). Empirically, the partitions implemented in the results section correspond exactly to alternative decompositions of these probability masses. Different empirical partitions correspond to integrating the same density over different subsets of the rank space. In particular, any aggregate mobility index  $\mathfrak{S}$  (e.g. Shorrocks, or trace-based measures) can be represented abstractly as:

$$\mathfrak{S} = \mathcal{F}(C_t, C_t, F_t, F_{t+1}).$$

Holding marginals fixed, changes in mobility are therefore driven entirely by changes in dependence parameters. To build intuition, it is useful to consider polar dependence regimes. Under perfect persistence,  $(U_{\Pi,t+1}, U_{W,t+1}) = (U_{\Pi,t}, U_{W,t})$ , so that  $R_{Y,t+1} = R_{Y,t}$  almost surely: the transition matrix becomes diagonal and reranking-based mobility measures attain their minimum. At the opposite extreme, if  $(U_{\Pi,t+1}, U_{W,t+1})$  is independent of  $(U_{\Pi,t}, U_{W,t})$ , then origins do not predict destinations: rows of the transition matrix become identical (equal to the destination distribution), and mobility indices attain the maximum compatible with the marginals. Intermediate cases help identify component drivers. For instance, if capital ranks are persistent while labor ranks are redrawn,  $U_{\Pi,t+1} = U_{\Pi,t}, U_{W,t+1} \perp (U_{\Pi,t}, U_{W,t})$ , then reranking originates exclusively from

labor dynamics, providing a benchmark for labor-driven mobility. From the probabilistic perspective, conditioning on large moves amounts to restricting attention to tail events for  $(U_{Y,t}, U_{Y,t+1})$ , or equivalently to extreme regions of the transition matrix. The empirical evidence that joint movements in capital and labor become more important for such transitions is therefore consistent with stronger comovement of component ranks in the tails, even when average upward mobility remains primarily labor-driven. These observations naturally raise a quantitative question: how would mobility change if the underlying strength of dependence were marginally different? At this stage, mobility has been reduced to a function of a small set of dependence parameters. Comparative statics therefore ask how marginal changes in these parameters modify observable transition patterns.

### B.3 Comparative statics in persistence

We now study how mobility reacts to marginal changes in dependence. The reason for doing so is that the copula parameters provide a compact summary of the strength of intertemporal association in ranks; understanding how mobility indices vary with those parameters allows us to translate statistical persistence into economically interpretable changes in reranking.

Let  $\theta$  denote a generic persistence parameter of the temporal copula. Under the Gaussian specification, for instance,  $\theta$  may correspond to one of the cross-time correlations such as  $\rho_{III}$  or  $\rho_{WW}$ , which directly regulate the strength of association between present and future ranks within each component. Since  $\xi$  can be written as an integral functional of the copula density, its derivative with respect to  $\theta$  can be expressed by differentiating under the integral sign:

$$\frac{\partial \xi}{\partial \theta} = \int \psi(\mathbf{u}; \theta) \frac{\partial c_{C_i}(\mathbf{u}; \theta)}{\partial \theta} d\mathbf{u},$$

where  $\psi$  weights each rank configuration by its contribution to the mobility statistic. This representation is useful conceptually: it makes clear that comparative statics are governed by how parameter changes reallocate probability mass across mobility-relevant regions (typically, toward or away from the diagonal of the transition ma-

trix).

The function  $\psi$  is entirely determined by the mobility index under consideration: it assigns to each origin–destination configuration the weight that the statistic gives to that event. For example, for the trace immobility measure  $\mathfrak{D} = \sum_i m_{ii}$ , one has  $\psi(\mathbf{u}) = \mathbf{1}\{R_{t+1} = R_t\}$ , so only transitions that remain on the diagonal receive weight. For upward mobility,  $\psi(\mathbf{u}) = \mathbf{1}\{R_{t+1} > R_t\}$  (this will be extended below). Hence comparative statics operate by shifting probability mass toward or away from the regions emphasized by  $\psi$ .

Under standard concordance orderings of copulas, stronger positive dependence increases the probability of remaining in the same rank neighborhood. Therefore, for a wide class of reranking-based mobility indices, such as Shorrocks-type measures, trace complements, or average off-diagonal mass, increases in persistence parameters reduce mobility (equivalently, increase immobility). Moreover, letting  $\theta_{\text{III}}$  and  $\theta_{\text{WW}}$  denote capital and labor persistence parameters, the derivatives  $\partial\mathfrak{S}/\partial\theta_{\text{III}}$  and  $\partial\mathfrak{S}/\partial\theta_{\text{WW}}$  quantify the marginal contribution of each income source to aggregate rigidity.

Under the Gaussian temporal copula, these statements can be made operational. Let the unit interval be partitioned into bins  $0 = p_0 < p_1 < \dots < p_K = 1$ . A transition from bin  $i$  to bin  $j$  in total income occurs when  $F_{Y_t}(Y_t) \in (p_{i-1}, p_i]$ ,  $F_{Y_{t+1}}(Y_{t+1}) \in (p_{j-1}, p_j]$ . In the latent Gaussian representation this corresponds to multivariate normal rectangle probabilities:

$$m_{ij} = \int_{\mathcal{R}_{ij}} \phi_{\mathbf{R}}(\mathbf{z}) d\mathbf{z},$$

where  $\phi_{\mathbf{R}}$  is the normal density with correlation matrix  $\mathbf{R}$ , and  $\mathcal{R}_{ij}$  is the set of latent realizations producing the required rank event.

Upward (downward) mobility can be expressed similarly; for instance, the probability of upward mobility from bin  $i$  is

$$\mathbb{P}(R_{Y_{t+1}} > i \mid R_{Y_t} = i),$$

which is computable from the conditional Gaussian law of  $\mathbf{Z}_{t+1}$  given  $\mathbf{Z}_t$ . These formulas make clear how comparative statics in  $\mathbf{R}$  translate into comparative statics in

$M$  and in aggregate indices.

We now derive four tractable implications under Gaussian rank dynamics: (i) diagonal mass as an explicit function of total-rank persistence, (ii) the probability of upward and downward moves (upper and lower diagonals), (iii) monotonicity of mobility with respect to persistence, and (iv) the link between dependence parameters and the composition of mobility in terms of capital- versus labor-driven moves.

Let  $R_{Y,t} \in \{1, \dots, K\}$  denote the total-rank bin and define the diagonal mass:

$$\mathfrak{D} := \sum_{i=1}^K m_{ii} = \mathbb{P}(R_{Y,t+1} = R_{Y,t}),$$

which is a natural *immobility proxy*. Define the latent total-rank score  $Z_{Y,t} = \Phi^{-1}(U_{Y,t})$  where  $U_{Y,t} = F_{Y,t}(Y_t)$ .

Define the latent total-rank score  $Z_{Y,t} = \Phi^{-1}(U_{Y,t})$ , where  $U_{Y,t} = F_{Y,t}(Y_t)$ . Even if the component ranks follow a Gaussian copula, the pair  $(U_{Y,t}, U_{Y,t+1})$  — and therefore  $(Z_{Y,t}, Z_{Y,t+1})$  — need not be Gaussian, because total income is a nonlinear aggregation of components. For the purpose of obtaining tractable expressions for transition probabilities, we approximate the joint law of  $(Z_{Y,t}, Z_{Y,t+1})$  by a bivariate normal distribution with correlation

$$\rho_Y := \text{Corr}(Z_{Y,t}, Z_{Y,t+1}),$$

where  $\rho_Y$  is the correlation implied by the full model, i.e., a function of the blocks of **R**.

The same logic applies to off-diagonal movements. Define the probability of upward and downward mobility as

$$\mathfrak{U} := \mathbb{P}(R_{Y,t+1} > R_{Y,t}), \quad \mathfrak{L} := \mathbb{P}(R_{Y,t+1} < R_{Y,t}),$$

so that  $\mathfrak{D} + \mathfrak{U} + \mathfrak{L} = 1$ . Under the Gaussian representation, these probabilities are again functions of the bivariate normal law of  $(Z_{Y,t}, Z_{Y,t+1})$  and therefore of  $\rho_Y$ . Intuitively, they correspond to the probability mass above and below the main diagonal in the latent space. Hence the empirical objects used in the decomposition of upward and downward movements map directly into well-defined regions of the copula.

For equal-probability bins ( $p_i = i/K$ ), define thresholds  $a_i = \Phi^{-1}(p_i)$ ,  $i = 0, \dots, K$ . Then diagonal mass admits the explicit form

$$\mathfrak{D}(\rho_Y) = \sum_{i=1}^K \left[ \Phi_2(a_i, a_i; \rho_Y) - \Phi_2(a_{i-1}, a_i; \rho_Y) - \Phi_2(a_i, a_{i-1}; \rho_Y) + \Phi_2(a_{i-1}, a_{i-1}; \rho_Y) \right], \quad (19)$$

where  $\Phi_2(\cdot, \cdot; \rho)$  denotes the standard bivariate normal cdf with correlation  $\rho$ . Hence  $\mathfrak{D}$  is directly computable from  $\rho_Y$ . For any copula parameter  $\theta$  entering  $\mathbf{R}$  (e.g.  $\theta = \rho_{\text{III}}$  or  $\rho_{\text{WW}}$ ), the effect on diagonal mass follows from the chain rule, which separates the mechanical link between total persistence and component persistence:

$$\frac{\partial \mathfrak{D}}{\partial \theta} = \frac{\partial \mathfrak{D}}{\partial \rho_Y} \cdot \frac{\partial \rho_Y}{\partial \theta}. \quad (20)$$

Because both  $\mathfrak{U}$  and  $\mathfrak{L}$  are complements of diagonal mass, their behavior with respect to persistence follows immediately from the same mechanism.

Moreover, since  $\mathfrak{U} + \mathfrak{L} = 1 - \mathfrak{D}$ , any increase in diagonal mass mechanically reduces total off-diagonal movement. In particular, under the Gaussian copula and equal-probability bins:

$$\frac{d}{d\rho_Y}(\mathfrak{U}(\rho_Y) + \mathfrak{L}(\rho_Y)) = -\frac{d}{d\rho_Y}\mathfrak{D}(\rho_Y) \leq 0,$$

so that aggregate directional mobility (upper plus lower diagonal mass) is nonincreasing in  $\rho_Y$ .

An analogous reasoning applies to the upper and lower triangles of the transition matrix. Let  $\mathfrak{U} := \mathbb{P}(R_{Y,t+1} > R_{Y,t})$ ,  $\mathfrak{L} := \mathbb{P}(R_{Y,t+1} < R_{Y,t})$  denote upward and downward mobility, respectively. Under the Gaussian representation these objects are also functions of the same latent correlation  $\rho_Y$ . Because probability mass shifts from the off-diagonal regions toward the diagonal as  $\rho_Y$  increases, both  $\mathfrak{U}$  and  $\mathfrak{L}$  are weakly decreasing in persistence.

Turning to monotonicity, consider a Shorrocks-type mobility index decreasing in diagonal mass, for instance  $\mathfrak{S} = 1 - \mathfrak{D}$  (or any monotone transform thereof). Then the next result formalizes that stronger rank persistence reduces mobility.

**Proposition B.1** (Diagonal mass monotonicity in  $\rho_Y$ ). *Under the Gaussian copula for  $(Z_{Y,t}, Z_{Y,t+1})$  and equal-probability bins,  $\mathfrak{D}(\rho_Y)$  is nondecreasing in  $\rho_Y \in [0, 1)$ . Hence*

$$\frac{d}{d\rho_Y}\mathfrak{S}(\rho_Y) \leq 0 \quad \text{for} \quad \mathfrak{S} = 1 - \mathfrak{D}.$$

*Proof sketch.* Each summand in (19) is the probability that two correlated normals fall into the same interval. For Gaussian pairs, increasing correlation increases concentration around the diagonal; equivalently, the probability of belonging to the same rank bin is increasing in  $\rho_Y$ . Summing over bins yields monotonicity of  $\mathfrak{D}$ .  $\square$

Combining (20) with Proposition B.1, sign predictions for  $\partial\mathfrak{D}/\partial\rho_{\text{III}}$  or  $\partial\mathfrak{D}/\partial\rho_{\text{WW}}$  reduce to sign predictions for  $\partial\rho_Y/\partial\rho_{\text{III}}$  and  $\partial\rho_Y/\partial\rho_{\text{WW}}$ , which can be established under benchmark restrictions (see below). While the previous results establish how persistence affects the overall amount of reranking, they do not reveal which income component is responsible for the observed movements. To answer this question, we now turn from aggregate magnitudes to the composition of transitions.

## B.4 Dependence parameters and decomposition shares

Aggregate indices summarize how much mobility occurs; the decomposition clarifies *how* it occurs. Recall:

$$\epsilon = \epsilon_\pi + \epsilon_w + B.$$

Define mover-type events:

$$C := \{\epsilon_\pi > 0, \epsilon_w \leq 0\} \quad (\text{capital-driven}), \quad \mathcal{W} := \{\epsilon_w > 0, \epsilon_\pi \leq 0\} \quad (\text{labor-driven}),$$

and *homoploutic events*:

$$\mathcal{H}^+ := \{\epsilon_\pi > 0, \epsilon_w > 0\}, \quad \mathcal{H}^- := \{\epsilon_\pi < 0, \epsilon_w < 0\}.$$

For any baseline conditioning set  $\mathcal{G}$  (e.g.  $R_{Y,t} = i$  or  $U_{Y,t} \in (p_{i-1}, p_i)$ ), define decomposition shares:

$$s_C(\mathcal{G}) = \mathbb{P}(C \mid \mathcal{G}), \quad s_{\mathcal{W}}(\mathcal{G}) = \mathbb{P}(\mathcal{W} \mid \mathcal{G}), \quad s_{\mathcal{H}^+}(\mathcal{G}) = \mathbb{P}(\mathcal{H}^+ \mid \mathcal{G}), \quad s_{\mathcal{H}^-}(\mathcal{G}) = \mathbb{P}(\mathcal{H}^- \mid \mathcal{G}).$$

Under the Gaussian temporal copula, component jumps can be expressed in rank space as:

$$\epsilon_\pi = Q_{\Pi,t+1}(U_{\Pi,t+1}) - Q_{\Pi,t+1}(U_{\Pi,t}), \quad \epsilon_w = Q_{W,t+1}(U_{W,t+1}) - Q_{W,t+1}(U_{W,t}).$$

If  $Q_{.,t+1}$  is strictly increasing, the sign of each component jump is determined by whether  $U_{\Pi,t+1} \geq U_{\Pi,t}$  and  $U_{W,t+1} \geq U_{W,t}$ . Hence mover-type probabilities reduce to copula probabilities of rank inequalities, e.g.:

$$\mathbb{P}(C \mid \mathcal{G}) = \mathbb{P}(U_{\Pi,t+1} > U_{\Pi,t}, U_{W,t+1} \leq U_{W,t} \mid \mathcal{G}). \quad (21)$$

In latent Gaussian space, this becomes a (conditional) multivariate normal probability over half-spaces:

$$\mathbb{P}(C \mid \mathcal{G}) = \mathbb{P}(Z_{\Pi,t+1} - Z_{\Pi,t} > 0, Z_{W,t+1} - Z_{W,t} \leq 0 \mid \mathcal{G}),$$

which is explicit given  $\mathbf{R}$ .

In the empirical section we operationalize these objects by classifying each observed move according to the signs of the component jumps, i.e. whether  $\epsilon_{\pi,i}$  and/or  $\epsilon_{w,i}$  are positive or negative.

In the rank-based model, these typologies correspond to probabilities of rank-inequality events under  $C_t$  (for instance  $U_{\Pi,t+1} > U_{\Pi,t}$  and  $U_{W,t+1} \leq U_{W,t}$  for “capital-driven” upward mobility). The unconditional frequencies reported in Section 4 can therefore be interpreted as empirical counterparts of these copula probabilities, possibly conditional on belonging to the upper or lower diagonal of the transition matrix. The dominance of labor-driven upward mobility and the prominence of capital-driven downward mobility thus translate into an asymmetric allocation of probability mass across regions of the temporal dependence structure.

This mapping from observed typologies to regions of the copula is crucial, because once mover categories are written as probability statements, their behavior can be studied through the dependence parameters of the temporal copula. Because mover categories correspond to regions of the rank space, their probabilities are determined by how the temporal copula allocates mass across those regions. Increasing persistence concentrates probability near the diagonal, thereby mechanically reducing the frequency of events that require sizable changes in the corresponding component rank.

As a limiting implication, it is important to distinguish between *sign changes* and

discrete reranking across bins, the latter being the notion underlying the transition-matrix decomposition used in the empirical analysis. When  $\rho_{\text{III}} \uparrow 1$ , the variance of  $Z_{\text{II},t+1} - Z_{\text{II},t}$  shrinks to zero, so the probability that capital crosses any fixed rank threshold converges to zero. Hence capital-driven transitions that rely on such threshold crossings vanish in the limit,  $s_c(\mathcal{G}) \rightarrow 0$ , unless labor dynamics simultaneously generate the move. Mobility therefore becomes concentrated in labor-driven or joint categories. Symmetrically, as  $\rho_{\text{WW}} \uparrow 1$ , labor-driven transitions disappear.

At the knife-edge boundary  $\rho_{\text{III}} = 1$ , capital ranks are perfectly fixed over time. In that case, homoploutic events that require  $\epsilon_\pi \neq 0$  also vanish, and any remaining mobility must be entirely attributed to labor dynamics.

These limiting cases clarify how the dependence parameters govern the composition of mobility, or *compositional mobility*, as labeled in the paper. A natural next step is to understand how the same parameters translate into implications for overall persistence in total income ranks. To obtain sharp and signable results, we now introduce a benchmark environment.

## B.5 Gaussian benchmarks

We now provide a transparent benchmark under which the effect of component persistence on total-rank persistence (and hence on mobility) can be signed analytically. Assume (i) no cross-component spillovers across time,  $\rho_{\text{IW}} = \rho_{\text{WI}} = 0$ , (ii) symmetric within-period alignment at each date, and (iii) monotonicity of the mapping from component ranks to the total rank  $U_{Y,t}$  in each argument. Under these conditions, increasing the latent persistence of one component strengthens concordance in that component without mechanically altering the other component's transition law. Let  $\rho_Y = \text{Corr}(Z_{Y,t}, Z_{Y,t+1})$  denote total-rank persistence. Then:

**Proposition B.2** (Component persistence raises total persistence). *Under the benchmark assumptions,*

$$\frac{\partial \rho_Y}{\partial \rho_{\text{III}}} > 0, \quad \frac{\partial \rho_Y}{\partial \rho_{\text{WW}}} > 0.$$

*Proof sketch.* Under the Gaussian temporal copula,  $(\mathbf{Z}_t, \mathbf{Z}_{t+1})$  is jointly Gaussian. Under (i)  $\rho_{\text{IW}} = \rho_{\text{WI}} = 0$ , increasing  $\rho_{\text{III}}$  increases concordance of the pair  $(Z_{\text{II},t}, Z_{\text{II},t+1})$

without changing the law of  $(Z_{W,t}, Z_{W,t+1})$ . Under (iii), the total-rank score  $Z_{Y,t} = \Phi^{-1}(U_{Y,t})$  can be written as an increasing measurable function of  $(Z_{\Pi,t}, Z_{W,t})$ , and similarly for  $t+1$ . For Gaussian vectors, increasing the correlation in one argument of an increasing function increases the correlation of the function itself (an instance of Gaussian association / monotone dependence; see, e.g., standard results on associated Gaussian vectors). Hence  $\partial\rho_Y/\partial\rho_{\Pi\Pi} > 0$ , and the same argument yields  $\partial\rho_Y/\partial\rho_{WW} > 0$ .  $\square$

Combining Proposition B.2 with Proposition B.1 yields the immediate mobility implication:

**Corollary 1** (Persistence reduces mobility). *Under the benchmark assumptions and for mobility indices decreasing in diagonal mass,*

$$\frac{\partial\mathfrak{S}}{\partial\rho_{\Pi\Pi}} < 0, \quad \frac{\partial\mathfrak{S}}{\partial\rho_{WW}} < 0.$$

Economically, when capital (labor) ranks become more persistent, individuals are less likely to experience reversals in that component. Since total income is increasing in both components, this mechanically raises the probability of remaining in the same total-income neighborhood, thereby reducing reranking mobility.

## C Alignment and dependence structure

The alignment coefficient  $B_i$  can be given a precise interpretation in terms of the dependence structure linking capital and labor income ranks. Let  $U_{\Pi,i,t} = F_{\Pi,t}(\Pi_{i,t})$  and  $U_{W,i,t} = F_{W,t}(W_{i,t})$  denote the marginal ranks of individual  $i$  in the capital and labor income distributions at time  $t$ . While the marginal distributions are fixed, the joint distribution of  $(U_{\Pi,t}, U_{W,t})$  is not uniquely determined and can be described by a copula  $C_t$ .

Fréchet–Hoeffding inequalities establish that any admissible copula must lie between two extremal dependence structures (see, e.g., (Nelsen, 2006)):

$$W(u, v) = \max\{u + v - 1, 0\} \leq C_t(u, v) \leq M(u, v) = \min\{u, v\}.$$

The upper bound  $M$  corresponds to perfect positive rank alignment (*comonotonicity*), where individuals high in capital income are also high in labor income. The lower bound  $W$  corresponds to maximal negative association (*countermonotonicity*), where high capital ranks are matched with low labor ranks.

These two polar cases induce different mappings between component ranks and total income ranks. Under comonotonicity, the ordering of total income closely mirrors the ordering of each component, so the rank of  $Y_{i,t}$  is almost entirely predictable from  $U_{\Pi,i,t}$  and  $U_{W,i,t}$ . Under countermonotonicity, instead, the sum  $\Pi + W$  reshuffles positions, weakening the link between marginal and total rankings.

The alignment coefficient  $B_i$  can therefore be interpreted as capturing how the observed economy positions itself between these feasible extremes. If capital and labor incomes were perfectly comonotonic and their marginal distributions identical, the mapping from component ranks to total ranks would be exact and  $B_i$  would vanish. Departures from zero reflect the extent to which the realized dependence structure modifies this mapping.

This interpretation can be made operational by constructing Fréchet envelopes for the counterfactual rank of total income at time  $t$ . Given the marginals  $F_{\Pi,t}$  and  $F_{W,t}$ , define the extreme feasible sums  $Y_t^M = Q_{\Pi,t}(U) + Q_{W,t}(U)$  and  $Y_t^W = Q_{\Pi,t}(U) +$

$Q_{w,t}(1 - U)$ , which correspond respectively to comonotonic and countermonotonic allocations. These generate two admissible cumulative distributions for total income,  $F_{Y,t}^M$  and  $F_{Y,t}^W$ .

For an individual with observed income  $Y_{i,t}$ , the implied feasible rank interval is therefore:

$$u_i^W = F_{Y,t}^W(Y_{i,t}) \leq F_{Y,t}(Y_{i,t}) \leq F_{Y,t}^M(Y_{i,t}) = u_i^M.$$

Mapping these ranks into time  $t+1$  produces a corresponding interval for the future reference threshold:

$$Q_{Y,t+1}(u_i^W) \leq Q_{Y,t+1}(F_{Y,t}(Y_{i,t})) \leq Q_{Y,t+1}(u_i^M).$$

Hence, the benchmark entering the income jump is itself constrained by the set of dependence structures compatible with the observed marginals. The empirical alignment coefficient measures where the realized mapping falls within this admissible region.

A convenient normalization is:

$$A_i = \frac{Q_{Y,t+1}(F_{Y,t}(Y_{i,t})) - Q_{Y,t+1}(u_i^W)}{Q_{Y,t+1}(u_i^M) - Q_{Y,t+1}(u_i^W)}, \quad A_i \in [0, 1],$$

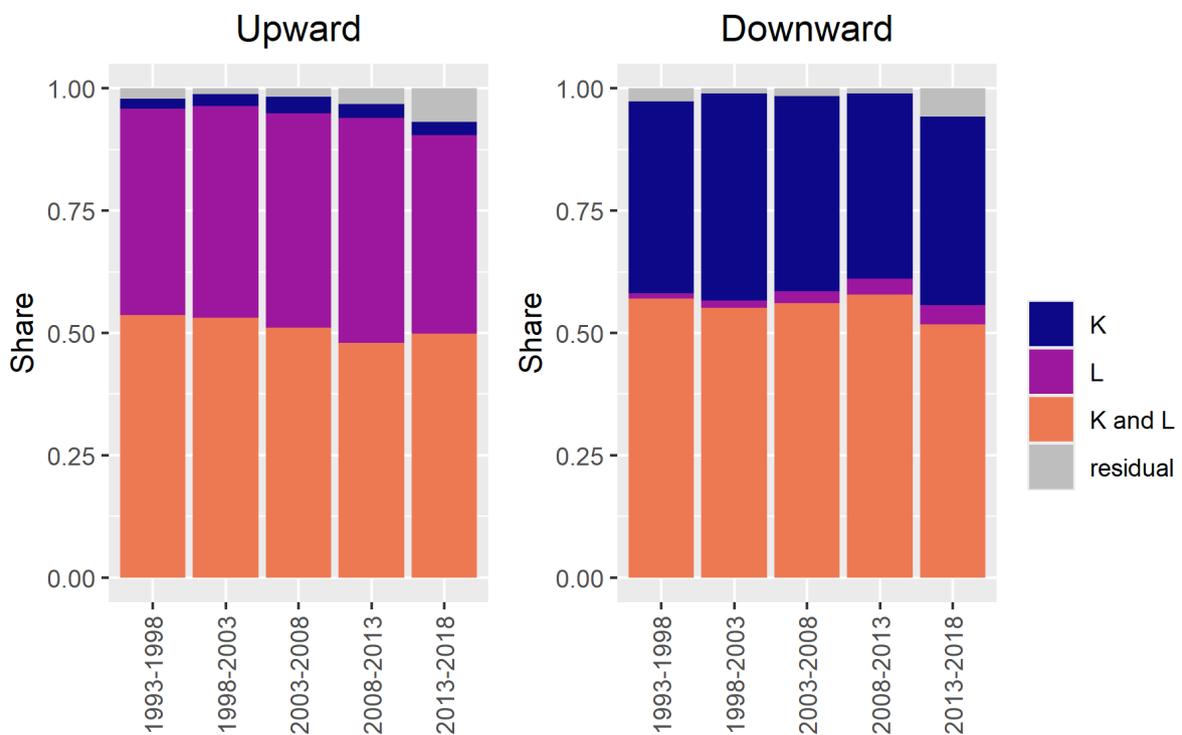
whenever the denominator is nonzero. Values of  $A_i$  close to one indicate comonotonic-type alignment, whereas values close to zero indicate countermonotonic-type alignment.

From this perspective,  $B_i$  can be viewed as an empirical statistic summarizing how far the observed economy is from perfect rank concordance between capital, labor, and total income distributions.

## D Additional Figures

This Appendix section reports additional figures that complement the paper's baseline analysis. Rather than estimating mobility over the full 1993–2018 sample, Figure 18 presents estimates of upward and downward mobility separately for consecutive five-year subperiods. Accordingly, the sample is partitioned into five non-overlapping bins. The resulting estimates are stable across subperiods, indicating that the observed patterns of upward and downward mobility are internally consistent and not driven by any particular time window.

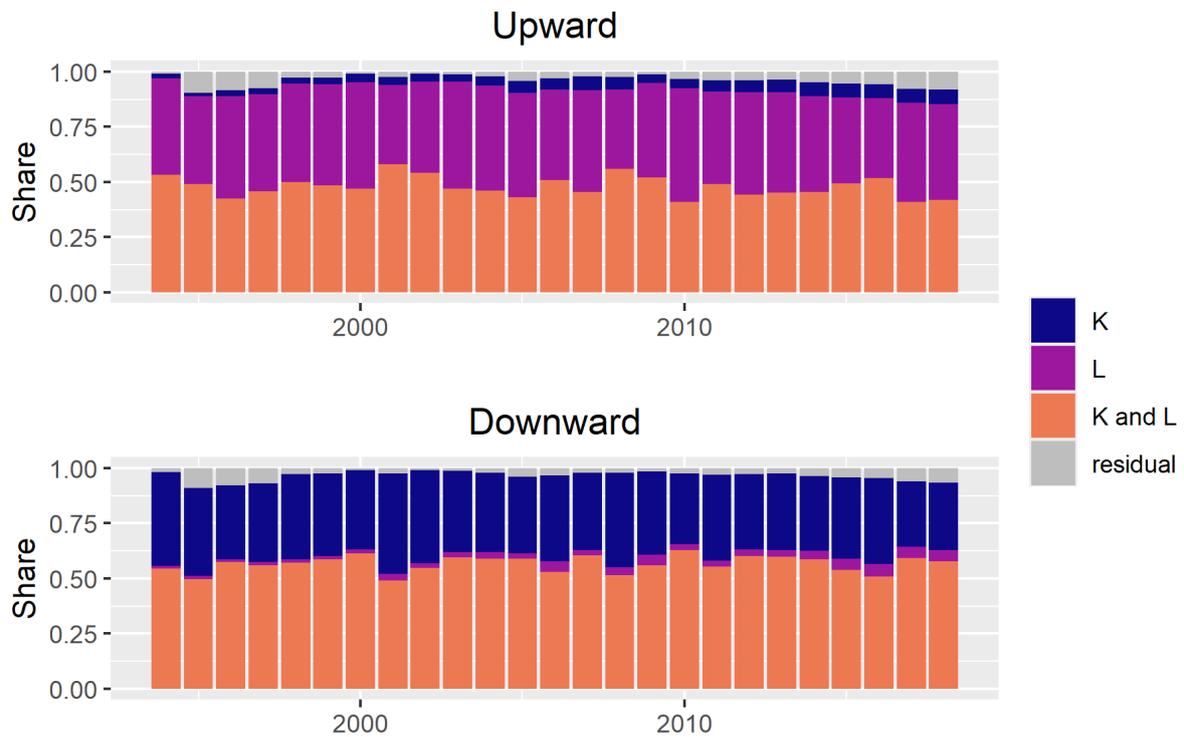
Figure 18: Results of decomposition of upward and downward mobility over time, 5 year periods



Note: Bars show upward and downward mobility decomposition over the period from year  $t - 5$  to  $t$ , for all years.

Figure 19 provides a more granular view of the mobility decomposition by plotting, for each year, the share of each mobility type. The year-by-year series exhibit no systematic trend, corroborating the baseline results in this finer-grained setting.

Figure 19: Results of decomposition of upward and downward mobility over time, 1 year periods

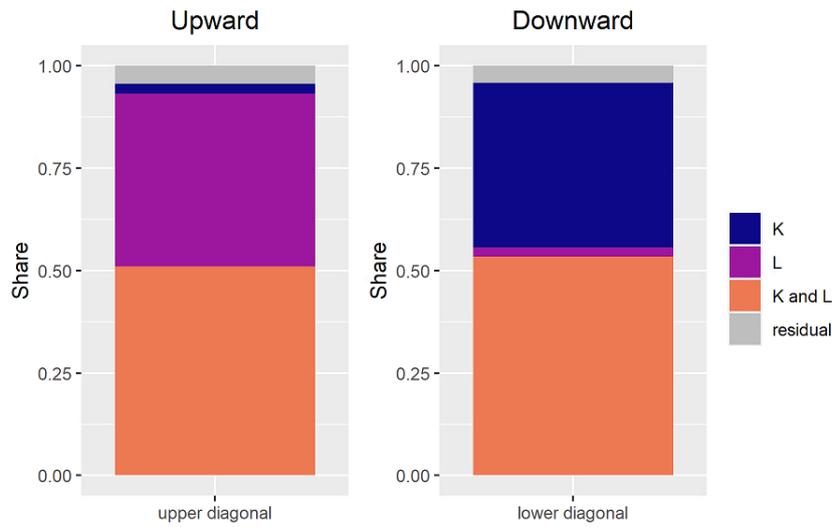


Note: Bars show upward and downward mobility decomposition over the period from year  $t - 1$  to  $t$ , for all years.

## D.1 Gender differences

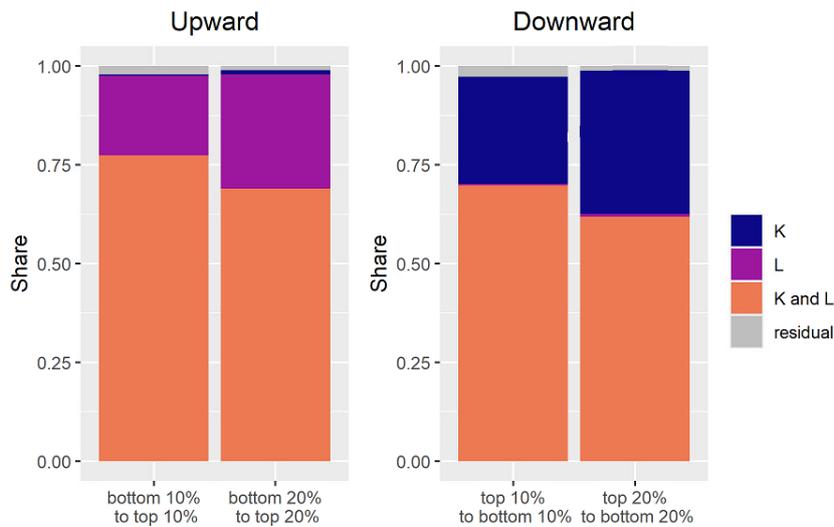
To assess gender differences, we re-estimate the analysis on an alternative cohort restricted to individuals who identify as men. Figures 20 and 21 report the corresponding results, which are qualitatively similar to those for the baseline sample.

Figure 20: Unconditional results of decomposition - Male cohort



Note: The graph displays the share of upward (downward) mobility explained solely by upward (downward) movement in capital income (K), only upward (downward) movement in labor income (L), and upward (downward) movement in both income components (K and L).

Figure 21: Conditional results of decomposition - Male cohort

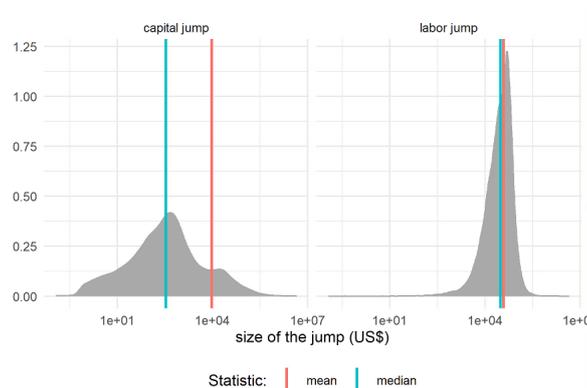


Note: The graph displays the share of upward (downward) mobility explained solely by upward (downward) movement in capital income (K), only upward (downward) movement in labor income (L), and upward (downward) movement in both income components (K and L), conditioned on moving from the bottom (top) 10% to the top (bottom) 10%, or from the bottom (top) 20% to the top (bottom) 20%, respectively.

## D.2 Joint upward mobility

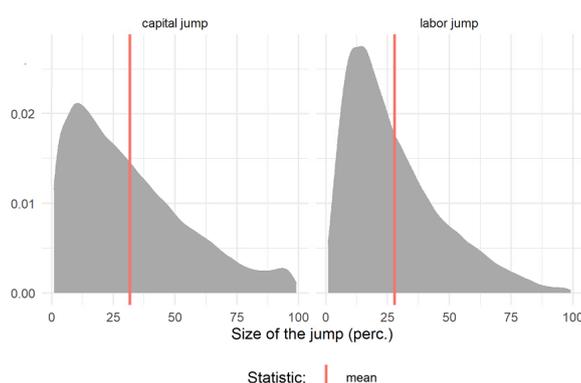
All our results indicate that aligned upward- and downward movement in capital and labor incomes contributes a large part to income mobility. For joint upward mobility, the median jump in labor income is significantly larger than the median jump in capital income. The figures below display the distribution of jumps unconditionally, both for absolute (Figure 22) and relative jumps (Figure 23), as well as conditional on starting (Figures 24, 25) and final decile (Figures 26, 27) for absolute jumps.

Figure 22: Joint upward mobility - Size of the jump (unconditional)



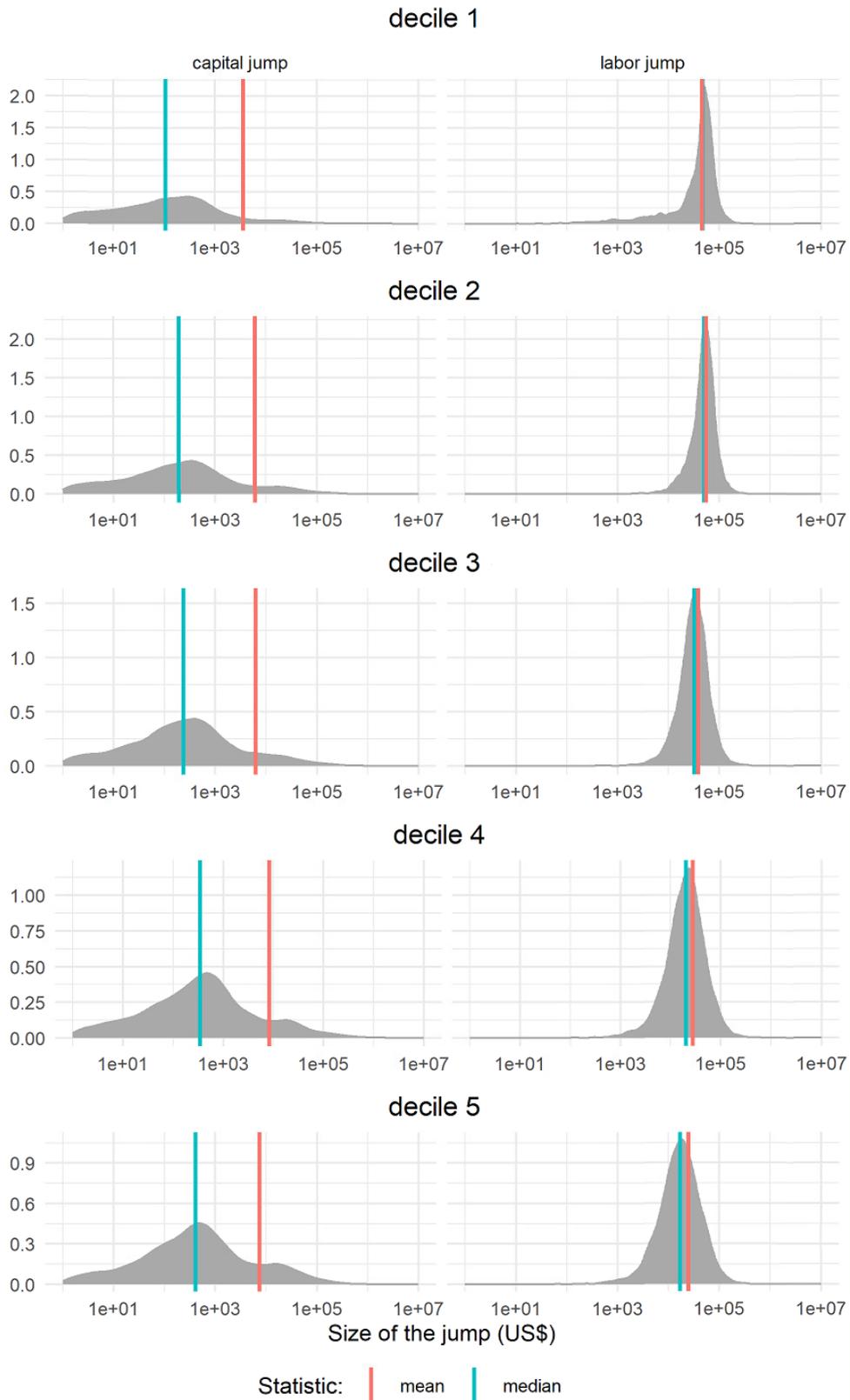
*Note:* The graph displays the distribution of absolute upward jumps in labor and capital income for those individuals which are part of our component 3, that is, those individuals moving upwards in the total income distribution because of simultaneous upward movements in capital *and* labor income.

Figure 23: Density of relative upward jumps in capital and labor income



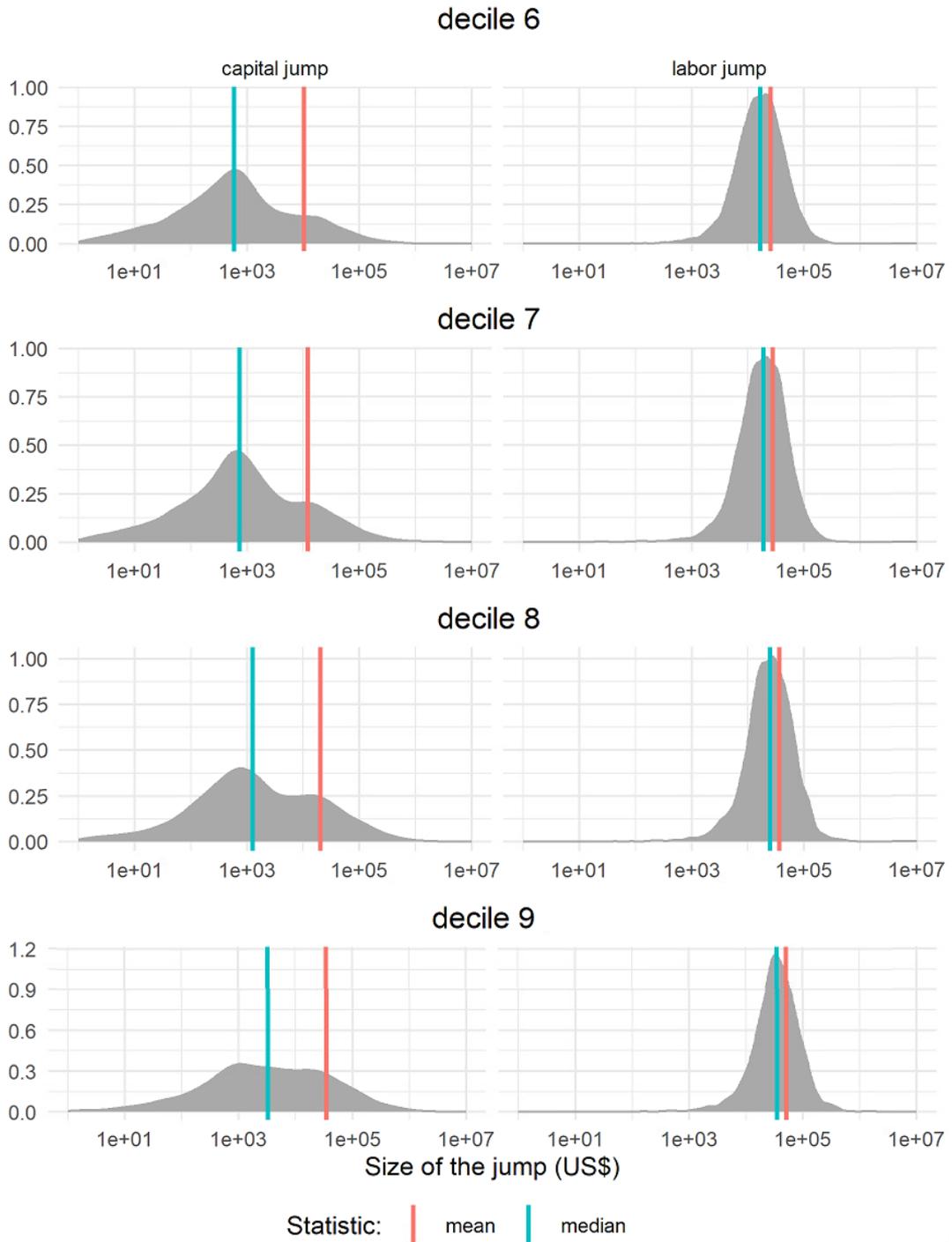
*Note:* The graph displays the distribution of relative upward jumps in labor and capital income for those individuals which are part of our component 3, that is, those individuals moving upwards in the total income distribution because of simultaneous upward movements in capital *and* labor income.

Figure 24: Joint upward mobility - Conditioning on initial decile



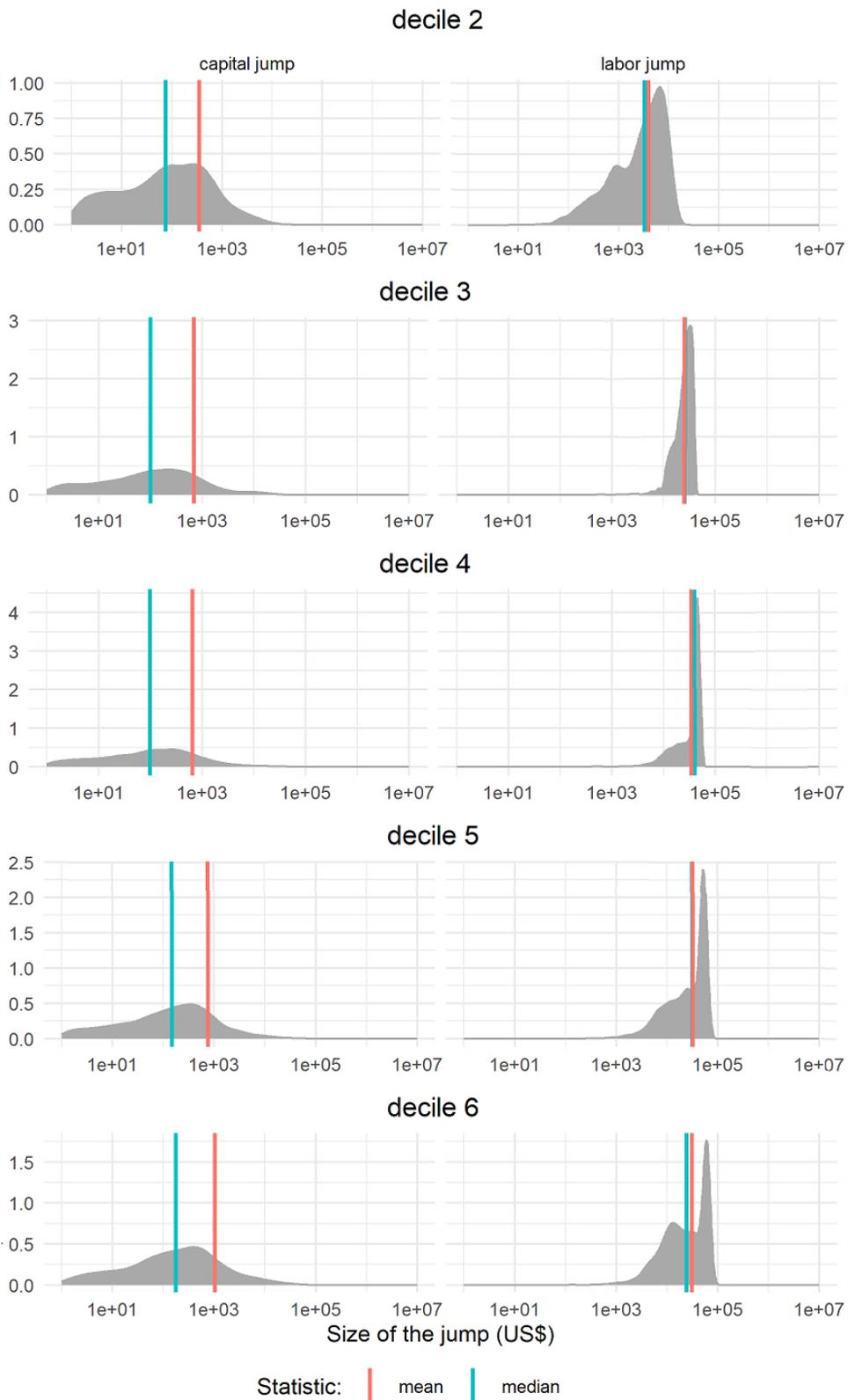
*Note:* The graph displays the distribution of upward jumps in labor and capital income for those individuals moving upwards in the total income distribution because of simultaneous upward movements in capital *and* labor income. Income jumps are displayed conditional on the initial decile in 1993.

Figure 25: Joint upward mobility - Conditioning on initial decile



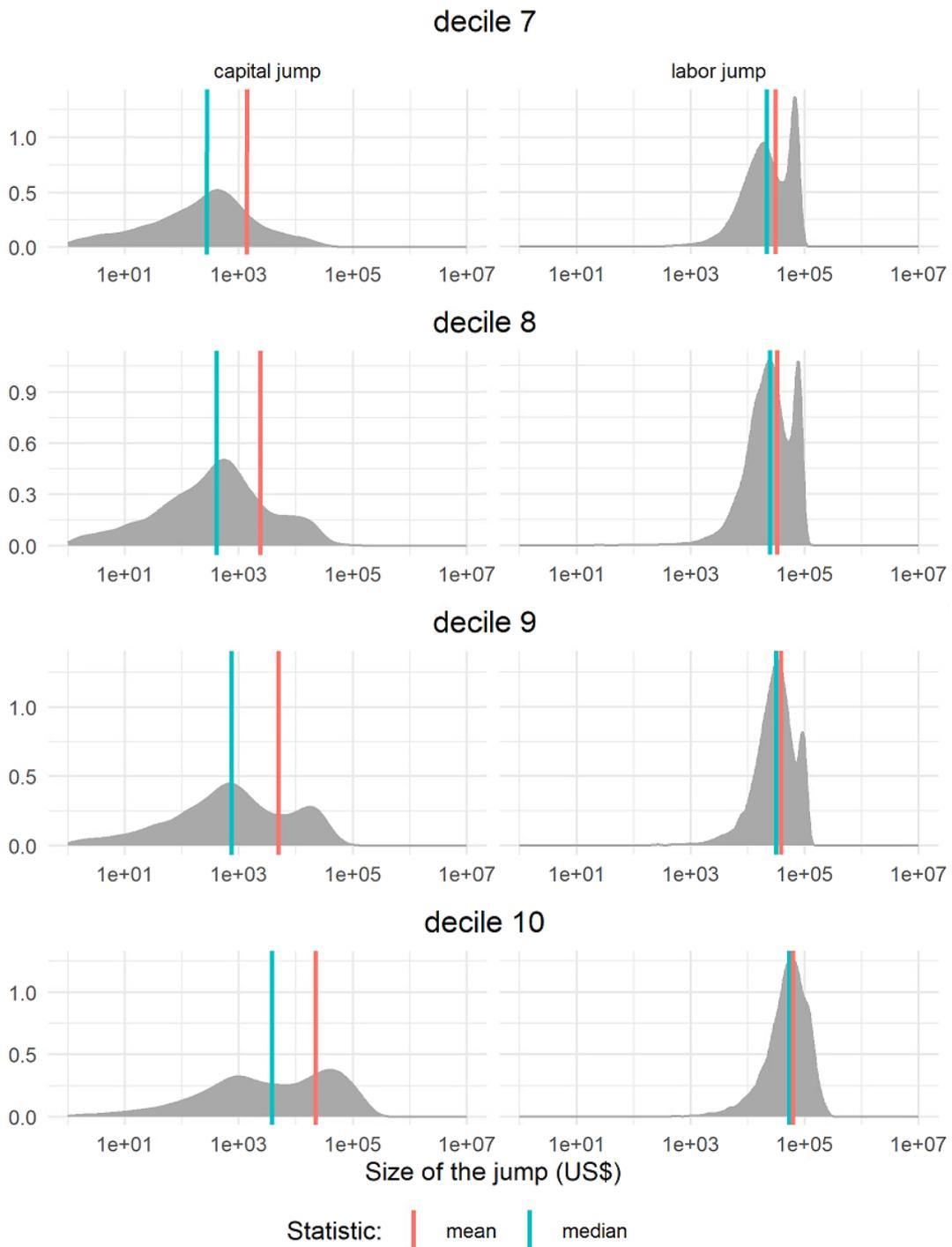
*Note:* The graph displays the distribution of upward jumps in labor and capital income for those individuals moving upwards in the total income distribution because of simultaneous upward movements in capital *and* labor income. Income jumps are displayed conditional on the initial decile in 1993. Decile 10 is omitted, because individuals initially in decile 10 cannot move further upward.

Figure 26: Joint upward mobility - Conditioning on target decile



*Note:* The graph displays the distribution of upward jumps in labor and capital income for those individuals moving upwards in the total income distribution because of simultaneous upward movements in capital *and* labor income. Income jumps are displayed conditional on the decile where an individual ends after 25 years. Decile 1 is omitted, because no individual can start below decile 1.

Figure 27: Joint upward mobility - Conditioning on target decile

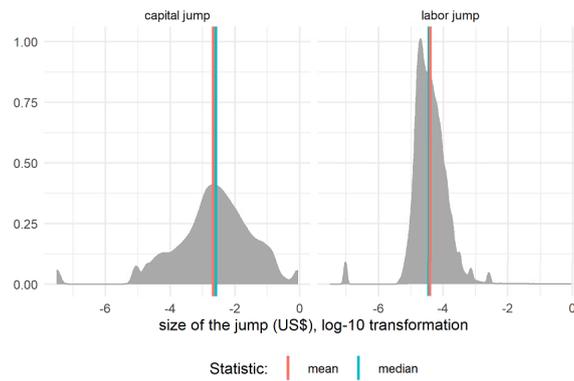


*Note:* The graph displays the distribution of upward jumps in labor and capital income for those individuals moving upwards in the total income distribution because of simultaneous upward movements in capital *and* labor income. Income jumps are displayed conditional on the decile where an individual ends after 25 years.

### D.3 Joint downward mobility

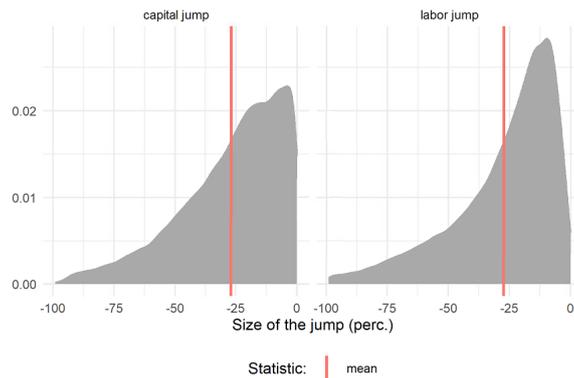
For joint downward mobility, the median absolute jump in labor income is much larger than the median absolute jump in capital income (as for the case of joint upward mobility). The figures below display the distribution of jumps unconditionally, both for absolute (Figure 28) and relative jumps (Figure 29), as well as conditional on starting (Figures 30, 31) and final decile (Figures 32, 33) for absolute jumps.

Figure 28: Joint downward mobility - Size of the jump (unconditional)



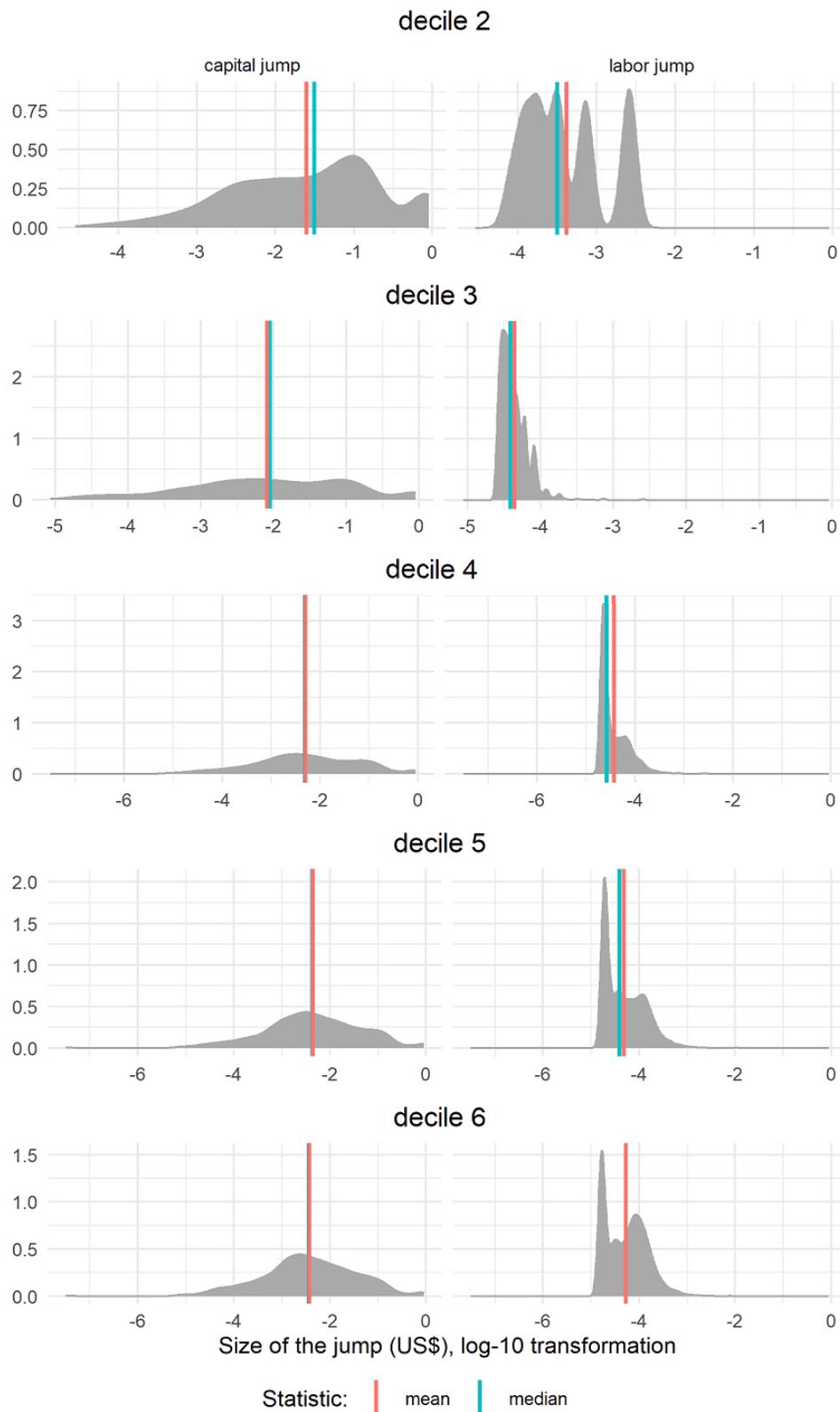
*Note:* The graph displays the distribution of absolute downward jumps in labor and capital income for those individuals which are part of our component 4, that is, those individuals moving down in the total income distribution because of simultaneous downward movements in capital *and* labor income.

Figure 29: Density of relative downward jumps in capital and labor income



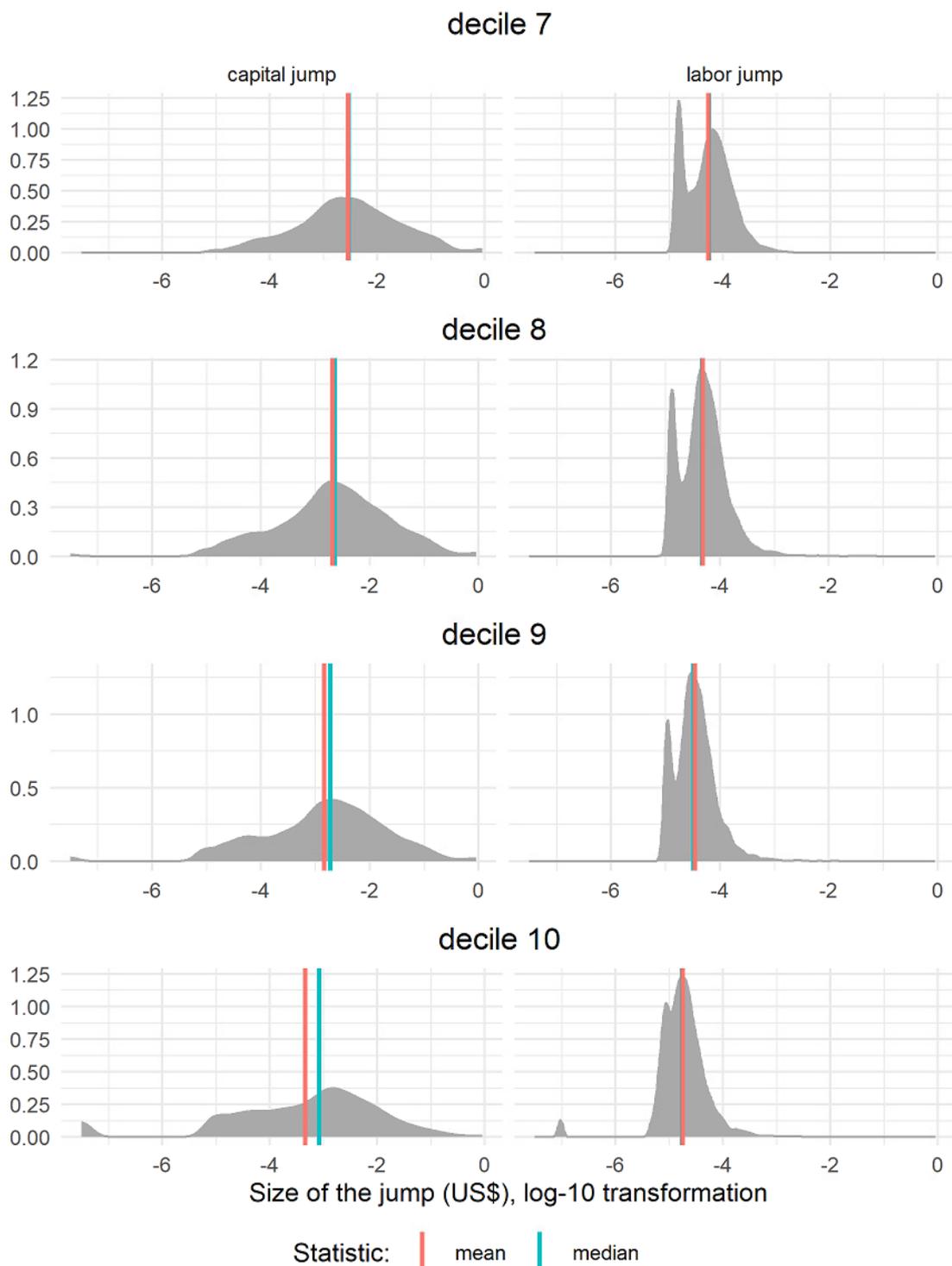
*Note:* The graph displays the distribution of relative downward jumps in labor and capital income for those individuals which are part of our component 4, that is, those individuals moving down in the total income distribution because of simultaneous downward movements in capital *and* labor income.

Figure 30: Joint downward mobility - Conditioning on initial decile.



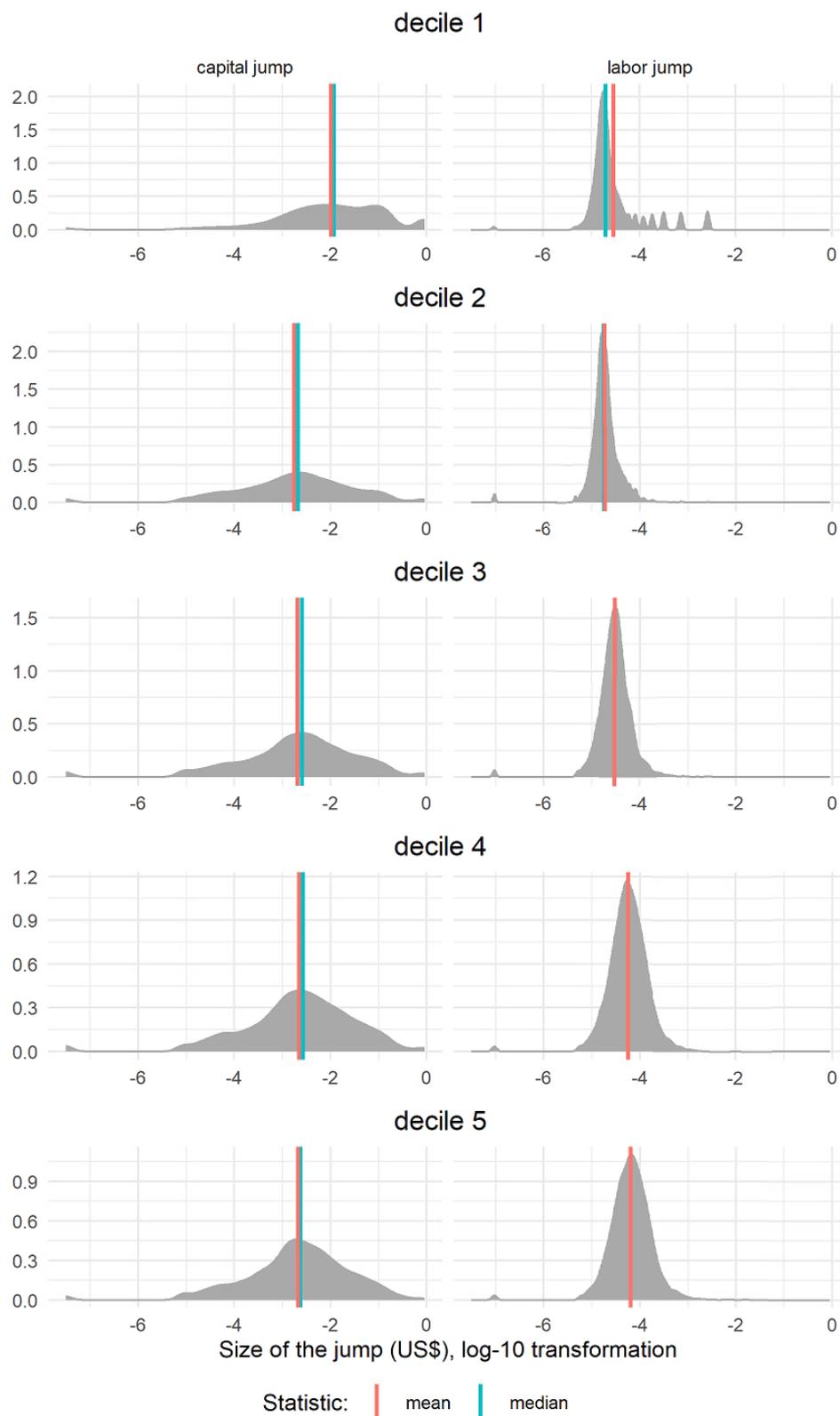
*Note:* The graph displays the distribution of downward jumps in labor and capital income for those individuals moving down in the total income distribution because of simultaneous downward movements in capital *and* labor income. Income jumps are displayed conditional on the decile where an individual starts in 1993. Decile 1 is omitted, as these individuals cannot move further down.

Figure 31: Joint downward mobility - Conditioning on initial decile



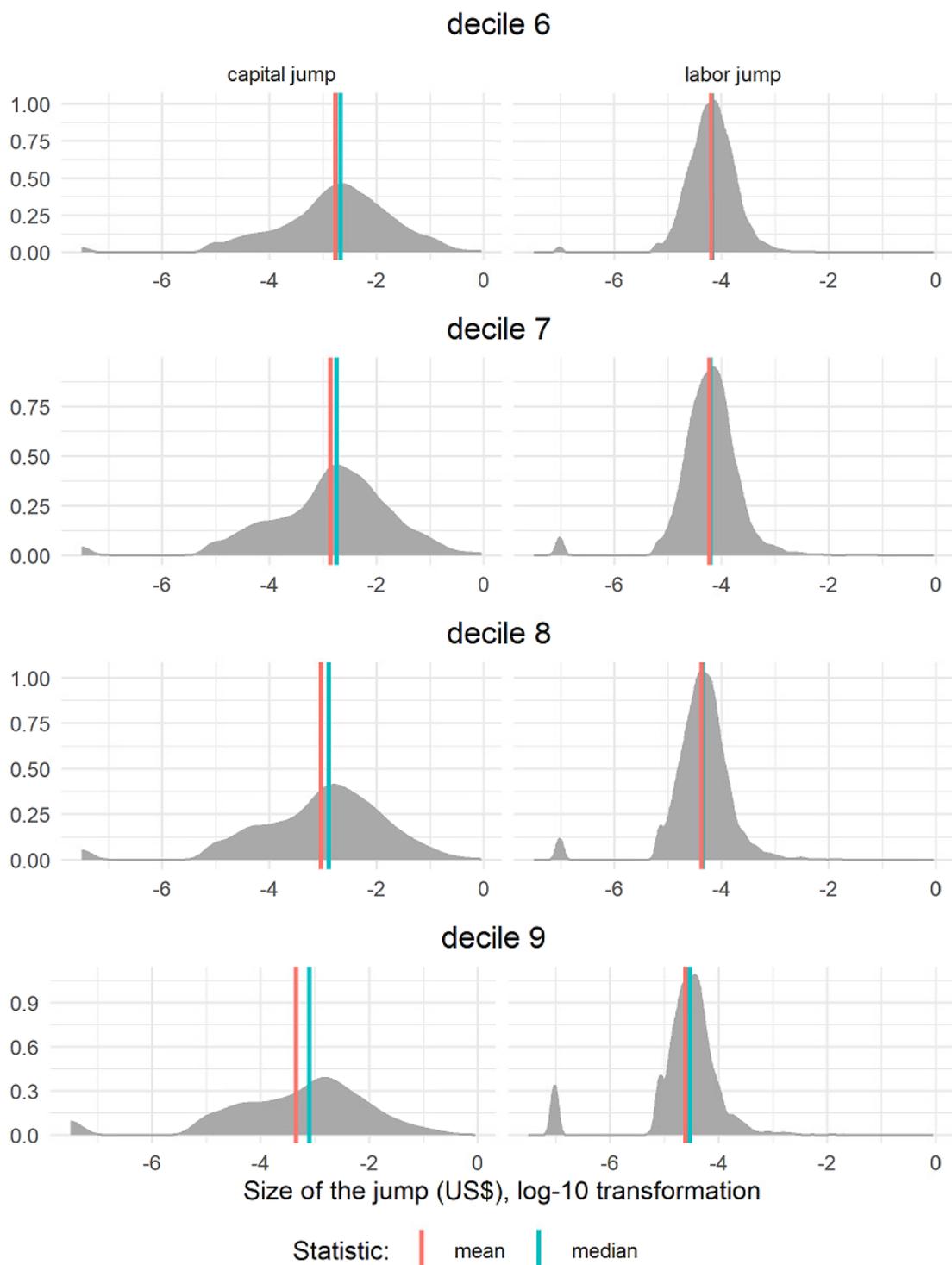
*Note:* The graph displays the distribution of downward jumps in labor and capital income for those individuals moving down in the total income distribution because of simultaneous downward movements in capital *and* labor income. Income jumps are displayed conditional on the decile where an individual starts in 1993.

Figure 32: Joint downward mobility - Conditioning on target decile



*Note:* The graph displays the distribution of downward jumps in labor and capital income for those individuals moving down in the total income distribution because of simultaneous downward movements in capital *and* labor income. Income jumps are displayed conditional on the decile where an individual ends after 25 years.

Figure 33: Joint downward mobility - Conditioning on target decile



*Note:* The graph displays the distribution of downward jumps in labor and capital income for those individuals moving down in the total income distribution because of simultaneous downward movements in capital *and* labor income. Income jumps are displayed conditional on the decile where an individual ends after 25 years. Decile 10 is omitted, as these individuals cannot have started above decile 10.