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A Micro Perspective on $r > g$

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Abstract

By exploiting large-scale administrative data on income and estimated personal wealth in Norway from 2010 to 2018, this paper establishes the first micro-level analysis of the difference between the real return on wealth and the real growth rate of total pre-tax income, across the entire net wealth distribution. We show that for the top 40% of the distribution, the aggregate $R-G$ of 1.8% underestimates its micro counterpart $r-g$, while the opposite happens for the bottom 60%. Moreover, for the bottom 50% of the net wealth distribution, it is indeed the case that $r < g$. In addition, we run a simulation exercise demonstrating that the full distribution of $r-g$—which has been shown to be positively associated with the position in the net wealth distribution—delivers a higher predictive power for the study of wealth inequality than simply focusing on the aggregate $R-G$. All results are robust to the exclusion of imputed rents from the income definition.

1 | INTRODUCTION

The publication of *Capital in the Twenty-first Century* (Piketty 2014) sparked a surge of interest in the study of wealth inequality and the relation between the rate of return on capital and the growth rate of income (for a recent survey, see König *et al.* 2020). The main take-away in Piketty (2014) and Piketty and Zucman (2014) is that whenever the rate of return on wealth overcomes the growth rate of income ($r > g$), wealth-rich individuals (the so-called *rentiers*) would accumulate wealth faster than individuals typically holding low or negative values of wealth and mainly relying on income, thus fostering wealth disparities in the longer run. The necessary assumptions for this prediction to hold, and the relation to economic theory, have been analysed by Hiraguchi (2019), Jones (2015), Mankiw (2015) and Stiglitz (2016). Important criticisms have also been raised about the Piketty (2014) interchangeable use of the terms 'capital' and 'wealth' (Stiglitz 2016). The author himself returns to the debate in Piketty (2015a, p. 48), clarifying that he does not consider '$r > g$ as the only or even as the primary tool … for forecasting the path of inequality in the twenty-first century. Institutional changes and political shocks … have played a major role in the past, and it will probably be the same in the future'.

In our view, a thorough understanding of $r > g$, and its predictive power, relevance and eventual limitations in the short and long run, hinges crucially on the variety of analyses carried out upon it. Jordà *et al.* (2019) use granular asset price data and find that the relation $r > g$ is a constant feature of their data in peacetime, for every country and period under analysis. For Norway in the period 1980–2015, they estimate that on average the real return on wealth is 6.55% higher than the real growth of GDP. Several studies have then attempted to switch focus from macro to micro, by decomposing the rate of return on wealth to allow heterogeneity of returns across the wealth distribution. On these lines, Fagereng *et al.* (2020) exploit the high quality of Norwegian individual-level data on wealth holdings to document the persistent heterogeneity of real rates of return on net worth across the distribution, even within asset classes. Furthermore, they show that rates of return on net worth are positively correlated with individuals' positions in the wealth distribution. Bach *et al.* (2020) use Swedish data and confirm that the expected return on (household) net worth is strongly persistent and increases with net wealth holdings.

Proceeding along these lines, we intend to fill a gap in the literature by providing the first micro-level empirical assessment of the difference between r and g, across the net wealth distribution. In addition, we provide a comparison between $r - g$ and its macro counterpart, which we refer to as $R - G$. By exploiting large-scale administrative data on personal wealth in Norway from 2010 to 2018, we show that the aggregate $R - G$ (with average 1.8% throughout the period) underestimates its micro counterpart $r - g$ for the top 40% of the wealth distribution, while the opposite happens for the bottom 60%. Interestingly, we also show that $r < g$ for the bottom 50% of the net wealth distribution. We show that this result is robust to changes in the income definition, by excluding imputed rents (or non-monetary income from housing).

Another important contribution of the paper is that the distribution of micro $r - g$ predicts a higher level of wealth inequality, in comparison to the aggregate $R - G$. This result is illustrated through a simulation exercise, in which we calibrate the income and wealth definitions with our data. In other words, although formally the macro $R - G$ can be expressed in terms of its micro counterpart $r - g$ through a difference between two unweighted averages, our empirical evidence indicates that the distribution of $r - g$ provides insights into the dynamics of wealth inequality that do not arise by focusing exclusively on mean variables.

We also analyse whether our evidence on the micro $r - g$ can be explained only by persistent heterogeneity across the net wealth distribution, or if we can attribute part of its variation to scale dependence. We show that after controlling for persistent heterogeneity, only a negligible fraction of the entire variation in $r - g$ (when moving up from the bottom decile to the top decile of the net wealth distribution) can be explained by scale dependence. Finally, we decompose personal wealth into its main components (housing and financial) to show that the share of financial wealth is positively correlated with $r - g$, while the opposite is true for housing wealth.

The paper is structured as follows. Section 2 presents the data and provides some descriptive statistics. Section 3 outlines the theoretical framework and explains our assumptions. Section 4 presents the main results, followed by discussion in Section 5, before Section 6 concludes the paper.

2 | DATA AND DESCRIPTIVE STATISTICS

Our analysis is based on Norwegian administrative tax records on income and wealth.[1] Norwegian administrative tax records represent a particularly reliable source of information since most components of income and wealth are reported by third parties, such as banks and employers, mitigating the risk of measurement errors and under-reporting deriving from self-reported income and wealth in surveys.

To ensure comparability of our results, we have chosen our sample in accordance with the Distributional National Accounts (DINA) guidelines produced by the World Inequality Database (Blanchet *et al.* 2021). Our baseline sample consists of the entire population of residents in Norway of age 20 years and above (although our results are not affected by considering a younger sample), between 2010 and 2018.

We focus on market incomes and pre-tax wealth holdings, hence we do not take into account the role of redistribution. For each resident individual i, the following definitions of personal wealth, capital income and total fiscal income are considered. All variables are measured on the last day of the year (31 December) and are at the level of individuals, not households.

- Gross wealth $gw_{i,t}$: estimated personal gross wealth, including estimated market values of real and financial capital. Real capital includes the estimated market value of the primary dwellings, secondary dwellings, land and buildings related to business activity (business assets). Financial capital includes cash, domestic deposits, foreign deposits, government and corporate bonds, bond funds and money market funds, shares in stock funds, other taxable capital abroad, and outstanding claims and receivables. Note that since entrepreneurs report private business wealth to the tax authorities as an assessed valuation of their shares, $gw_{i,t}$ therefore includes a portion of unrealized capital gains on financial wealth.
- Private debt $d_{i,t}$: private debt to Norwegian and foreign creditors (consumer debt, student debt and long-term debt), including debt related to shares in real estate companies.
- Net wealth $w_{i,t}$: gross wealth $gw_{i,t}$ minus private debt $d_{i,t}$.
- Capital income $k_{i,t}$. Taxable property income includes share dividends, interest income on bank deposits and on domestic and foreign assets, interest on loans to companies, and realized capital gains. From this, we subtract realized capital losses and interest expenditures, to obtain capital income net of the cost of capital. To this base definition of net capital income, we add imputed rents, and unrealized capital gains on housing wealth. We compute imputed rents as a constant fraction of the percentile estimated value of housing wealth by employing a nominal interest rate 3%, as done in Bø (2020). We follow Fagereng *et al.* (2020) and compute unrealized capital gains on housing as the yearly difference in housing wealth of the previous year.[2]
- Total fiscal income $y_{i,t}$. Fiscal pre-tax income includes employee income, taxable and tax-free transfers, capital incomes, and net income from self-employment. Net self-employment income is the sum of self-employment income in agriculture, forestry and fishing, and self-employment income from other industries received during the calendar year, less any losses. It also includes sickness benefits paid to the self-employed.

The full sample varies from approximately 3.67 million individuals in 2010 to 4.12 million in 2018, and it sums up to 35.09 million throughout the period. For more information, see Table A1 in the Appendix, showing summary descriptive statistics describing the sample. All variables are subsequently adjusted for inflation based on the CPI, and expressed from here onwards in real terms. In each year, the totals for our series of estimated net wealth fully match those from the national accounts household sector wealth statistics provided by Statistics Norway.[3]

Figure 1 plots our main variables of interest in the period 2011–2018: gross (gw_t) and net ($w_t = gw_t - d_t$) wealth, capital (k_t) and total income (y_t) (pooled across the years 2011–2018, in billions of Norwegian kroner, at constant prices, 2015 CPI), all ranked across the net wealth distribution. The first year of our baseline sample 2010 is not included because a series of capital gains in housing wealth are computed as yearly differences starting from 2011. Note that due

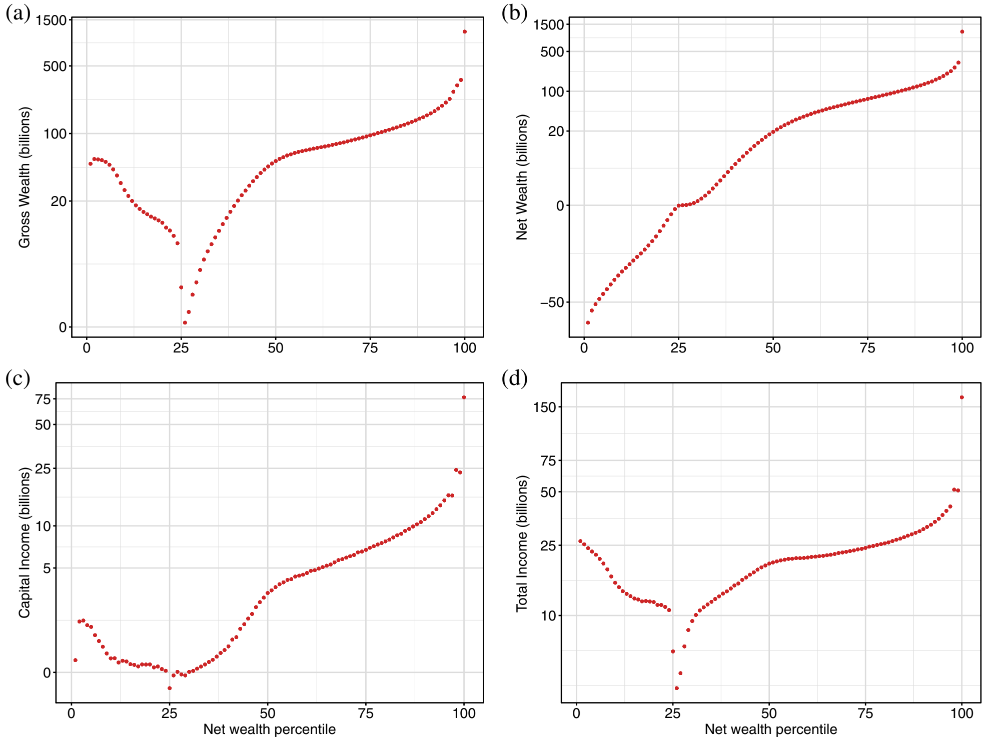

FIGURE 1 Gross and net wealth, capital and total income: 2011–2018. *Notes*: Panel (a) shows the series of gross wealth; panel (b) shows the series of net wealth; panel (c) depicts capital incomes; and in panel (d), total incomes are drawn. All variables are given in billions of Norwegian kroner, constant prices, 2015 CPI, pseudo-log scale, ranked across the net wealth distribution and pooled across the years 2011–2018. The bottom part of the gross wealth distribution appears to be decreasing since individuals are ranked according to their net wealth holdings.

to indebtedness in the lower deciles (mostly long-term debt), the net wealth turns positive only around the 25th percentile.

Regarding conventional inequality measures, the gross wealth distribution exhibits a Gini coefficient 0.52 across the period (2011–2018), while the Gini coefficient for the net wealth distribution rises to 0.61. The Gini coefficient for the distribution of pre-tax capital incomes exhibits a level of 0.58, while it drops to 0.28 for the series of pre-tax total income. (This value is slightly higher than estimations of the Gini coefficient of total income for Norway by Statistics Norway, which lie between 0.237 in 2011 and 0.251 in 2018.)[4] The discrepancy between our estimates of the Gini coefficient and those of Statistics Norway lies in our capital income definition, which is net of interest expenditure and includes imputed rents and unrealized capital gains in housing wealth. Proceeding with measures of wealth concentration, Figure 2 shows that the top 10% receive a slightly increasing share, in between 50% and 55% of the total net wealth in our sample. The same is true for the top 1%, increasing its share from approximately 20% to 24% in the final year. A top 1% share of slightly above 20% is in line with previous estimates of top wealth shares in Norway, documented in Epland and Kirkeberg (2012).

Figure 3 shows the different components of personal wealth in Norway across the net wealth distribution. Notably, the wealthy own higher shares of financial and business assets with respect to the rest of the distribution. At the same time, liabilities are substantially high throughout the distribution, highlighting the high level of households' indebtedness in the Norwegian economy.

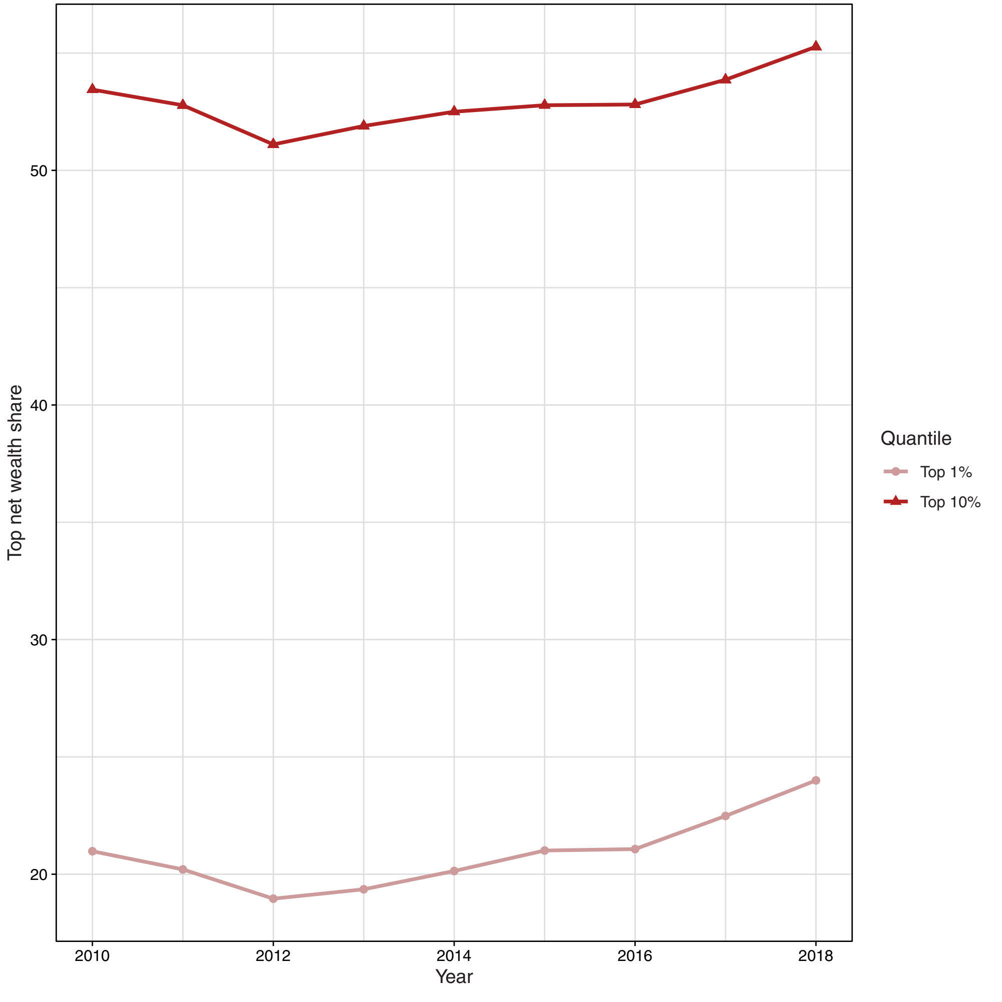

FIGURE 2 Shares of net wealth for the top 1% and top 10%, 2010–2018. *Notes*: This figure plots the 2010–2018 time series for the shares for the top 10% and top 1% of the net wealth distribution.

A remark should be made about our definition of wealth. In the unified framework developed by Piketty and Zucman (2014) and Blanchet *et al.* (2021), national wealth is the sum of public and private wealth, where private wealth consists of the net wealth of private households (personal wealth) and of non-profit institutions serving households (NPISH). In this work, we focus purely on personal wealth, hence abstracting from the net wealth of NPISH and public wealth. This choice allows, however, a more precise and assumption-free mapping between the aggregate and micro variables, since we would be obliged to perform imputations in order to allocate public wealth back to individuals.

Finally, we indicate some details about sample restriction related to the estimation of r, g and $r - g$ in Section 4. We trim the full sample by excluding values of r and g lying outside the accepted range [−30%, +30%]. Trimming is performed in a conservative spirit. This ensures that our findings are not driven by a few outliers or measurement errors. Our baseline trimming results in excluding 9% of the full sample. The results are robust to significantly milder trimming or even to no trimming.[5]

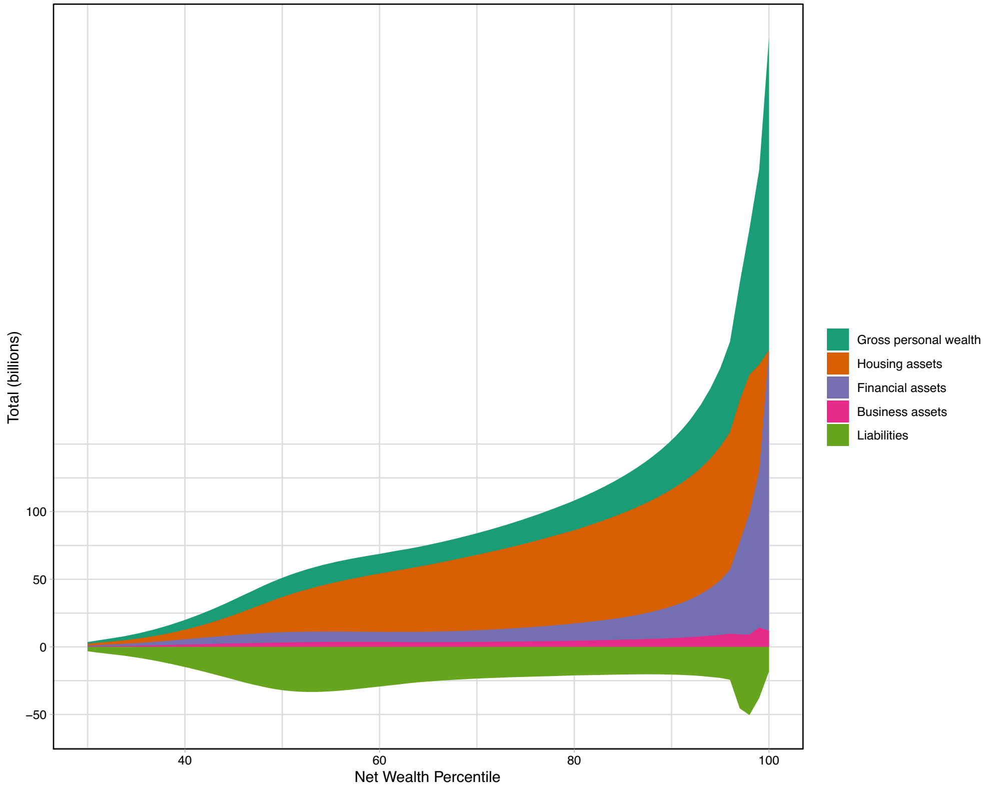

FIGURE 3 The composition of wealth, 2010–2018. *Notes*: The composition of wealth in Norway across the net wealth distribution. Averages (pooled across the years 2010–2018) per percentile, nominal values.

3 | CONCEPTUAL FRAMEWORK

This section outlines our framework and clarifies our assumptions. In recent years, the academic debate on the meaning and relevance of $r - g$ has produced a variety of conceptual frameworks, with different implications for the the study of wealth inequality (Jones 2015; Khieu 2021). Although returns on wealth (or net worth) have been defined in rather similar ways in the literature (Jordà *et al.* 2019), there has been more variety in approaches to the way g is conceptualized. On the one hand, Piketty (2015a, p. 73) defines g as the rate of economic growth of an economy. In his view, 'a higher gap between r and g works as an amplifier mechanism for wealth inequality for a given variance of other shocks' (Piketty 2015a, p. 75). Mankiw (2015) considers instead a stylized economy with two kinds of agents (workers and capitalists), with workers consuming only earnings plus transfers from the government (c_w), and the consumption of capitalists (c_k) being determined purely by net-of-tax returns on the capital stock (per capitalist). The ratio of capitalists' consumption to workers' consumption (c_k/c_w) then becomes a proxy for the inequality level in this economy. In this setting, policymakers can curb inequality by choosing a positive level for the capital tax τ.

Regardless of these different definitions, the common intuition is that an increasing $r - g$ would imply a higher growth rate of the stock of wealth for the wealthy rich, relative to what happens for individuals relying (mostly) on labour income, hence widening disparities in the economy (assuming a positive degree of inequality in ownership of assets). Although we believe that the stylized model in Mankiw (2015) is helpful to frame the relevance of $r - g$, our study is primarily empirical and we therefore allow our income definition to depart from a dichotomic division of society into workers and capitalists. Our income definition is

$$\begin{cases} Y_t = rW_{t-1} + Y_t^L, \\ Y_t = (1+g)\,Y_{t-1}, \\ W_t = W_{t-1} + sY_t, \end{cases} \tag{1}$$

where $rW_{t-1} \equiv K_t$ represents the individual's capital incomes (including capital gains) at time t, while Y_t^L is non-capital income, hence a sum of employee income and net income from self-employment, plus taxable and tax-free transfers. The (gross) wealth stock at time t is equal to wealth at time $t-1$ plus a savings component sY_t. In other words, we allow a fraction of income—i.e. $(1-s)\,Y_t$—to be consumed.

3.1 | The aggregate *R* and *G*

We enter now the core of our framework, by defining the aggregate real rate of return R_t as the yearly ratio between end-of-period total capital income K_t at time t (net of interest expenditure, the cost of capital), and end-of-period total gross wealth GW_{t-1} at $t-1$. Following Fagereng *et al.* (2020), we express the real rate of return as a share of (real) gross wealth to avoid negative values for individuals with negative net wealth, and to avoid measurement errors from attributing infinite returns to individuals with very low values of net wealth:

$$R_t = \frac{K_t}{GW_{t-1}} = \frac{\sum_{p=1}^{P} k_{p,t}}{\sum_{p=1}^{P} gw_{p,t-1}}, \tag{2}$$

where k_p and gw_p are the percentile sums of individual-level net capital incomes and gross wealth. Our estimate of the rate of return in Norway, pooled across the years 2012–2018, exhibits average 4.6%. Furthermore, we define the real aggregate growth rate G of total fiscal income as

$$G_t = \frac{Y_t - Y_{t-1}}{Y_{t-1}} = \frac{\sum_{p=1}^{P} y_{p,t} - \sum_{p=1}^{P} y_{p,t-1}}{\sum_{p=1}^{P} y_{p,t-1}}. \tag{3}$$

Our estimate of the growth rate G of the total fiscal income in Norway gives average 2.8%. Note for the sake of clarity that this includes population growth rate 1%, which is constant throughout the years under analysis.[6] This implies that our estimate for the aggregate $R-G$ in Norway over the considered time period amounts to 1.8% (or 0.8% when abstracting from population growth).

3.2 | A micro-level perspective on *r* and *g*

The target of this paper is to present the first micro-level empirical estimates of the difference between the real rate of return and the growth rate of total fiscal pre-tax income $(r-g)$ across the entire net wealth distribution, in relation to its aggregate counterpart $(R-G)$. To this end, we define r as the percentile average (for each $p = 1, \ldots, P$) of the ratio between individual capital income and gross wealth:

$$r_{p,t} = \frac{\sum_{i=1}^{N_p} k_{i,t}}{\sum_{i=1}^{N_p} gw_{i,t-1}}, \tag{4}$$

where N_p is the total number of individuals in each percentile p. The standard deviation of the micro r_p is 27.8%, slightly higher than the standard deviation 22.1% estimated for unweighted returns to wealth in Fagereng *et al.* (2020) (although their analysis is based on the years 2004–2015, hence it overlaps with our empirical exercise for only a few years).

As shown in equation (1), we define g as the growth rate of personal total income:

$$g_{p,t+1} = \frac{y_{p,t+1} - y_{p,t}}{y_{p,t}} = \frac{\sum_{i=1}^{N_p} y_{i,t+1} - \sum_{i=1}^{N_p} y_{i,t}}{\sum_{i=1}^{N_p} y_{i,t}}, \tag{5}$$

where N_p is the total number of individuals in each percentile p of the net wealth distribution.[7]

Before we move to the next section, where we present the results for the micro $r - g$, let us highlight, for the sake of clarity, the analytical expression linking the macro $R - G$ to its micro counterpart. Recall the definition of the aggregate R in equation (2), which can be expressed as a function of the micro r_p as

$$R_t(r_{p,t}) = \frac{\sum_{p=1}^{P} k_{p,t}}{\sum_{p=1}^{P} gw_{p,t-1}} = r_{1,t}S_1 + \cdots + r_{p,t}S_p, \tag{6}$$

where $S_p = gw_{p,t}/GW_t$ is the wealth share within percentile p (hence $\sum_{p=1}^{P} S_p = 1$). In other words, the aggregate rate of return R can be decomposed into the unweighted average of the micro rates at the percentile level. A similar decomposition can be applied to the growth rate of total income G of equation (3), yielding the following result for the functional form of the difference between the macro $R - G$ and its micro counterpart:

$$\begin{aligned} R_t(r_{p,t}) - G_t(g_{p,t}) &= (r_{1,t}S_1 + \cdots + r_{p,t}S_p) - (g_{1,t}\lambda_1 + \cdots + g_{p,t}\lambda_p), \\ &= (r_{1,t}S_1 - g_{1,t}\lambda_1) + \cdots + (r_{p,t}S_p - g_{p,t}\lambda_p), \end{aligned} \tag{7}$$

where $\lambda_p = y_p/Y$ is the share of total income within percentile p (hence $\sum_{p=1}^{P} \lambda_p = 1$).

4 | RESULTS

Results from our main analysis are presented below. From here onwards, notice that since our series on unrealized capital gains on housing wealth begins in 2011, growth rates in income across the net wealth distribution will be available from 2012 to 2018. Therefore we restrict our main analysis to this range of years.

4.1 | Wealth–income ratios

We start by estimating the household sector's aggregate wealth–income ratio β for each t:

$$\beta_t = \frac{GW_t}{Y_t} = \frac{\sum_{p=1}^{P} gw_{p,t}}{\sum_{p=1}^{P} y_{p,t}}, \tag{8}$$

where gw_p and y_p are the percentile sums of individual-level real gross wealth and total income, respectively, and in addition, we derive the micro β values for the pooled sample given by $\beta_p = gw_p/y_p$ to analyse how the wealth–income ratio evolves across the net wealth distribution.

Panel (a) of Figure 4 shows how the aggregate wealth–income ratio in our sample evolves over the period considered. The average throughout the period is 371% (marked by a horizontal dashed line in both panels). Our aggregate wealth–income ratio grows non-monotonically from 320% in 2012 to slightly below 440% in 2018.[8]

Panel (b) of Figure 4 instead shows that the wealth–income ratio varies significantly across the distribution of net wealth. For the top 30%, the wealth–income ratio lies above the aggregate average 371%, while the opposite is true for the bottom 70%. The top 1% of the net wealth distribution exhibits a wealth–income ratio of approximately 700%, indicating a high degree of heterogeneity across the distribution, especially at the very top.

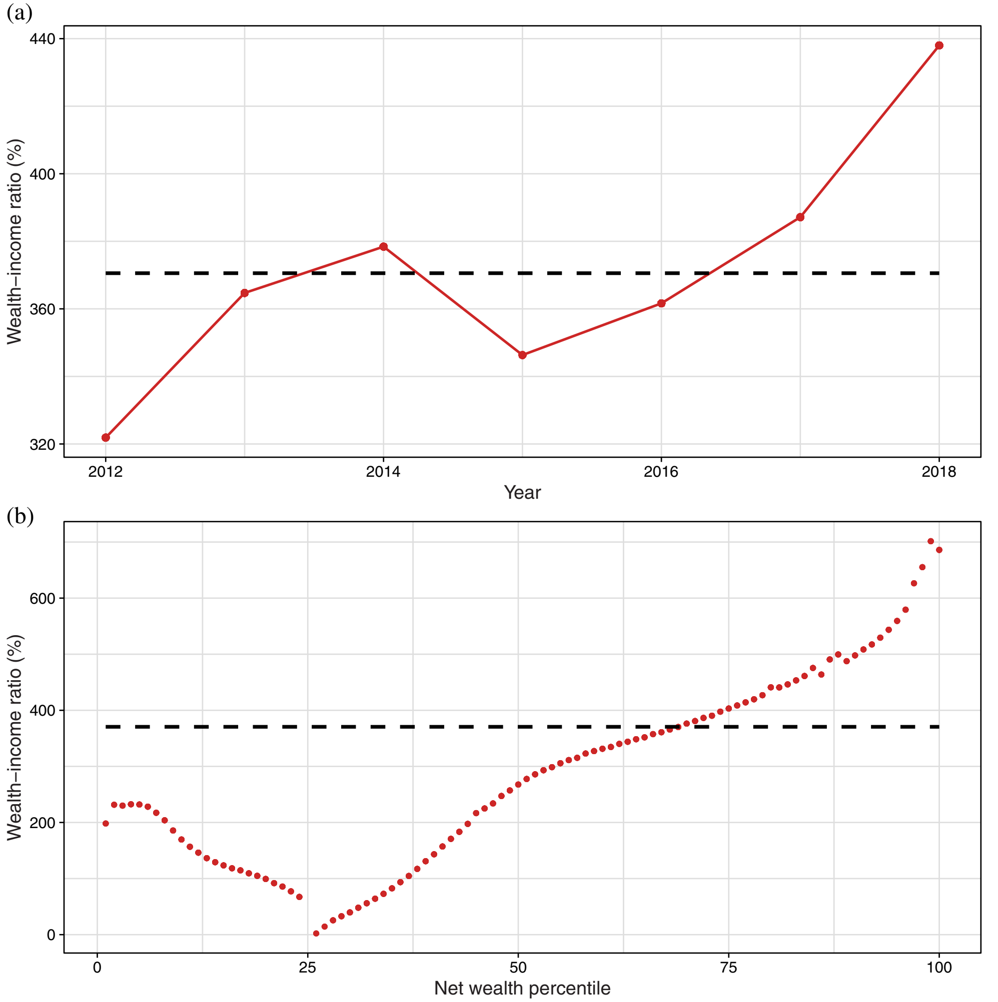

FIGURE 4 Wealth–income ratio: aggregate and by percentile. *Notes*: Panel (a) shows the aggregate wealth–income ratio across the years 2012–2018, while panel (b) shows the micro wealth–income ratio across the distribution of net wealth. The average is 371%, marked by a horizontal dashed line in both panels.

4.2 | The distribution of $r-g$

In Figure 5, we present the main finding of our study, namely, the full distribution of $r-g$.

Panels (b) and (c) of Figure 5 show respectively how r and g evolve across the net wealth distribution, pooled across the years (2012–2018). The horizontal dashed lines in panels (b) and (c) represent the G and R levels. In panel (c), it is shown that micro g fluctuates around its aggregate counterpart G for the whole distribution of net wealth. Interestingly, income growth seems to be slightly negatively correlated with wealth, as the bottom 30% in the net wealth distribution tends to have moderately higher growth rates than the rest of the distribution. In fact, in Norway, the bottom net wealth owners are typically highly indebted, but do not necessarily earn low incomes. In our data, the degree of correlation between income and wealth is negative for the bottom 30% in the net wealth distribution, while it is positive and close to 1 for the rest. In contrast, panel (b) of Figure 5 shows that r exhibits higher heterogeneity and a positive degree of covariation with the position in the net wealth distribution, in line with Fagereng *et al.* (2020).

Merging together panels (b) and (c) of Figure 5 gives us the evidence shown in panel (a). Panel (a) shows the difference between the *micro* rates of return on wealth r, and the *micro* growth rate of personal total fiscal income g, across the net wealth distribution. The horizontal dashed line represents the aggregate $R-G$, with average 1.8% throughout the period, as shown in the

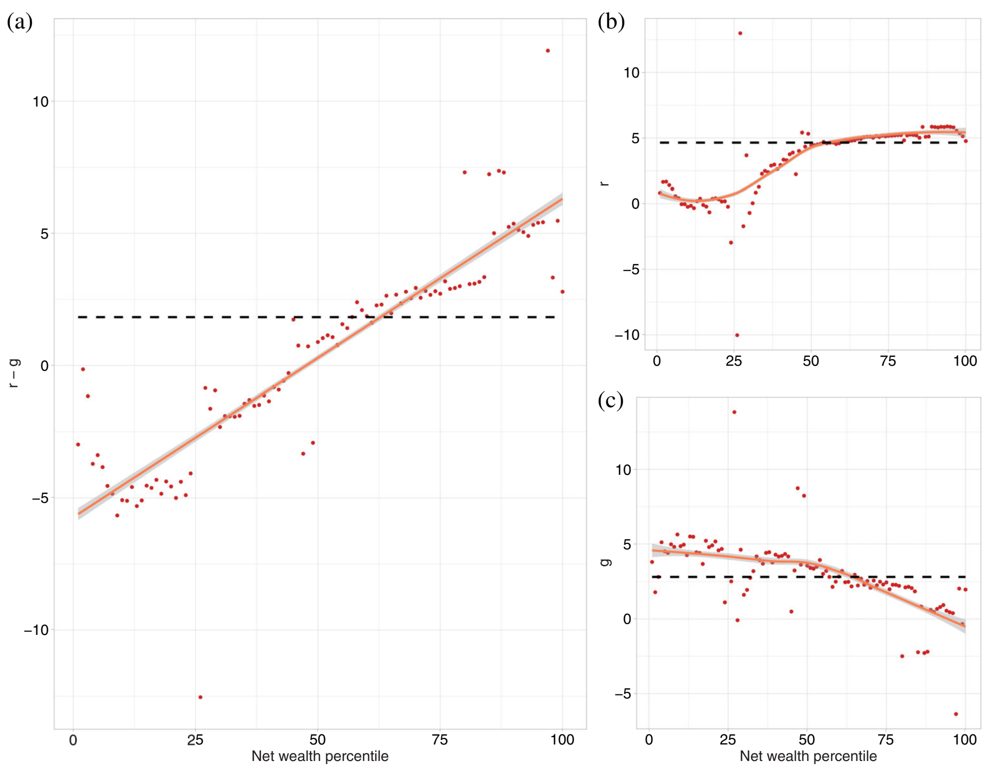

FIGURE 5 The distribution of $r-g$. *Notes*: Panel (a) shows the difference between the rate of return r and the growth rate of personal total fiscal income g, across the net wealth distribution, in percentage terms, averaged over the years 2012–2018. The horizontal dashed line represents the aggregate $R-G$ with average 1.8% throughout the period. A linear fit is drawn for illustrative purposes throughout the distribution of $r-g$. Panels (b) and (c), respectively, show how r and g evolve across the net wealth distribution over the period considered. The horizontal dashed lines represent the aggregate levels for R (panel (b)) and G (panel (c)). A local polynomial non-parametric fit for each of the two distributions is drawn.

first subsection of Section 3, in line with the macro evidence shown in Jordà *et al.* (2019), namely that $r > g$ appears as a regularity in all countries. The aggregate $R - G$ of 1.8% overestimates its micro counterpart $r - g$ for approximately the bottom 60% of the net wealth distribution, while the opposite happens for the top 40%. Interestingly, panel (a) of Figure 5 shows that for the bottom 50% of the population, it is indeed the case that $r < g$. In theoretical models, $r < g$ is usually related to dynamic inefficiency, since one would need to invest more than returns to wealth to keep the stock of wealth growing as the flows of total income. In this work, $r < g$ indicates that for half of the population under analysis, growth rate of income overcomes the returns on wealth, and it is explained by the fact that highly indebted individuals (the bottom of the net wealth distribution) receive reasonably high earnings to sustain their private debts. This empirical fact is in line with Norway ranking among the OECD countries with the highest ratio of household debt to net disposable income in the last decade. This implies that the evidence of $r < g$ for such a large fraction of the population might not necessarily be a feature of economies with lower household indebtedness ratio.

How robust are these results from abstracting from population growth? Recall that in our sample, population growth is constant at a rate of approximately 1% throughout the years under analysis. In other words, both the aggregate g and the percentile-specific micro version of g would be 1% *lower* when subtracting the population growth rate. This will therefore shift *upwards both* the aggregate and the micro version of $r - g$ by 1%. However, the steepness of the micro $r - g$ across the wealth distribution—and therefore the gap between the aggregate g and the percentile-specific micro version of g—would remain constant across the wealth distribution.

In our view, the above evidence on $r - g$ is complementary to the compelling evidence on returns (r), shown in Fagereng *et al.* (2020). In other words, it is not at all obvious that the dynamics of $r - g$ can be disentangled only by looking at the returns. Indeed, $r - g$ grows with wealth as returns do, but it does so also because g does not show a strong positive correlation with the position in the net wealth distribution. Hypothetically, a positive correlation between g and net wealth rank stronger than what we observe for r would imply a decreasing $r - g$ across the wealth distribution, which is the opposite of our result. Overall, we claim that this evidence demonstrates that an assessment of how the difference between the real rate of return on wealth minus the real income growth is distributed delivers more insights than just focusing on mean variables. Therefore micro $r - g$ qualifies as a more informative measure to highlight distributional aspects. This statement will be tested and quantified through the simulation exercise in Section 5. In addition, the extent to which the covariation between $r - g$ and position in the net wealth distribution is due to heterogeneity or scale effects (or both) will be analysed further in Section 5.

4.3 | Robustness checks

To what extent is the evidence shown in Figure 5 robust to changing the income definition? As mentioned before, to ensure comparability of our results, we have built our sample and chosen an income definition in accordance with the DINA guidelines produced by the World Inequality Database (Blanchet *et al.* 2021). In addition, we have aimed to produce evidence that can be traced back directly to the data that are made available from Statistics Norway, without undertaking additional arbitrary assumptions.

That said, we have complemented the basic definition of capital income with one additional component, namely imputed rents (or non-monetary income from housing), whose relevance is often disputed. (For a recent evaluation of the relationship between imputed rents and inequality, see List 2022). As we explained in Section 2, we compute imputed rents as a constant fraction of the percentile estimated value of housing wealth by employing a nominal interest rate 3%. This is the same procedure employed in Bø (2020), where the same register data sources are utilized.

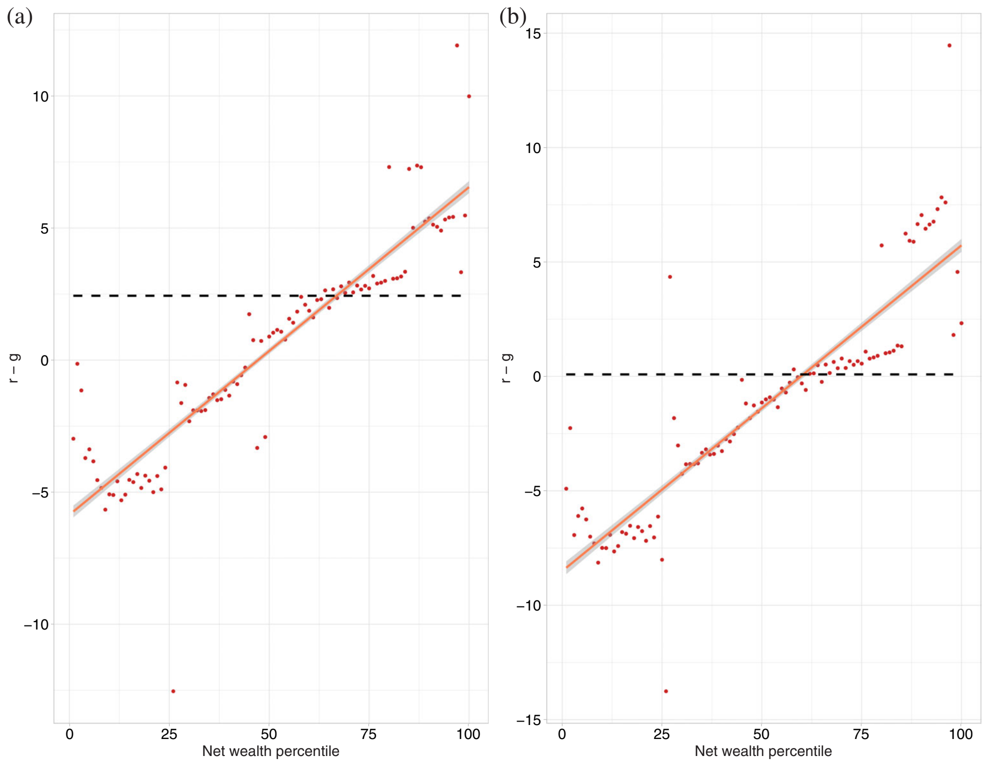

FIGURE 6 The distribution of $r - g$ excluding imputed rents. *Notes*: Panel (a) shows the difference between the rate of return r and the growth rate of personal total fiscal income g, across the net wealth distribution, in percentage terms, averaged over the years 2012–2018. The horizontal dashed line represents the aggregate $R - G$ with average 1.8% throughout the period. A linear fit is drawn for illustrative purposes throughout the distribution of $r - g$. Panel (b) shows panel A with a different income concept, i.e. excluding imputed rents.

How would our results change if we exclude imputed rents? To this end, we perform a robustness check by abstracting from including non-monetary income from housing in the definition of capital income. This means that imputed rents are also excluded from total fiscal (pre-tax) income. A graphical comparison between $r - g$ with imputed rents (panel (a)), and without imputed rents (panel (b)) is offered in Figure 6.

Although the magnitude of the aggregate $R - G$ is reduced by approximately 2 percentage points, the positive degree of covariation between $r - g$ and position in the net wealth distribution appears to be robust to excluding imputed rents. This is explained by the fact that the exclusion of imputed rents shifts down the level of capital income, but with similar magnitudes across the net wealth distribution, hence not leading to substantial changes on the difference between rates of return on wealth and growth rates of total income.

5 | DISCUSSION

5.1 | A simulation exercise

Does micro $r - g$ lead to higher or lower wealth inequality compared to its aggregate counterpart $R - G$? Berman *et al.* (2016) study the dynamics of wealth inequality through a theoretical exercise based on realistic modelling of the wealth distribution. In a subsequent related study, Berman and Shapira (2017) analyse the asymptotic properties of the wealth distribution, concluding that for $r > g$, the wealth distribution constantly becomes increasingly inegalitarian. This subsection sheds light on the relevance of our main result for the dynamics of wealth inequality. To this end, we carry out a simulation calibrated on our data,[9] and we draw a counterfactual comparison between two scenarios.

Assume that the dynamics of income and wealth accumulation at time t can be summarized as

$$\begin{cases} W_{p,t} = W_{p,t-1} + s_p Y_{p,t}, \\ Y_{p,t} = r_p W_{p,t-1} + Y^L_{p,t}, \\ Y^L_{p,t} = (1+g_p) Y^L_{p,t-1}, \end{cases} \tag{9}$$

where the wealth stock for percentile p at time t is equal to wealth at time $t-1$ plus a savings component $s_p Y_{p,t}$.[10] We assume a gross saving rate s_p, that increases monotonically with net wealth percentiles from 0% to 50%, in line with recent estimates of saving rates across the wealth distribution in Norway (Fagereng *et al.* 2019).[11] Income $Y_{p,t}$ is defined as the sum of capital income (including capital gains) $r_p W_{p,t-1}$ and labour income $Y^L_{p,t}$. Furthermore, we assume that labour income grows at the percentile-specific rate g_p.[12] We assume, for simplicity, a fixed rank for both income and wealth distributions. Rearranging equations (9), we obtain the following system of equations to conduct our simulation:

$$\begin{cases} Y^L_{p,t} = (1+g_p) Y^L_{p,t-1}, \\ W_{p,t} = W_{p,t-1} + s_p(r_p W_{p,t-1} + Y^L_{p,t}). \end{cases} \tag{10}$$

Let us draw two scenarios from here onwards. In scenario A, we let the income of each percentile of the wealth distribution y_p grow in every period at the average growth rate estimated in our main results section ($G = 2.8\%$). We assume that each percentile of the wealth distribution w_p is characterized by a rate of return equal to the aggregate rate of return ($R = 4.6\%$). Scenario A thus depicts a situation in which $R - G = 1.8\%$ is constant across the wealth distribution, as shown by the horizontal line drawn in Figure 5. In scenario B, we instead introduce heterogeneity by allowing income across different percentiles to grow at the percentile level income growth rates (i.e. $g = g_p$). We apply the micro rates of return ($r = r_p$) to the percentiles of the wealth distribution.

The results of the simulation exercise are presented in Table 1. The univariate Gini coefficient for net wealth increases only slightly after 150 time periods under scenario A (the one in which aggregate $R - G$ is employed). On the other hand, introducing heterogeneity by allowing percentiles of income and wealth distribution to grow at different rates, as in scenario B, delivers a different outcome. In fact, the Gini coefficient of net wealth increases by 41%, stabilizing at higher levels than for scenario A. In our view, the gap between the two scenarios highlighted by this simulation exercise underlines the importance of considering heterogeneity for wealth inequality dynamics. Results are consistent when looking at top 1% wealth shares instead of Gini coefficients. Moreover, the general findings are robust when assuming a constant saving rate (in this case equal to 7%; see Fagereng *et al.* 2019) or a different income concept excluding imputed rents.

Overall, the main message of this thought experiment is that considering a homogeneous $R - G$ underestimates the magnitude of wealth inequality with respect to taking into account heterogeneity by employing $r - g$. In our view, this result is in line with the theoretical insights in Stiglitz (2016), extending the Solow model by introducing variable returns to capital to explain the emergence of income and wealth inequality, and in line with Gabaix *et al.* (2016), studying the importance of scale dependence in growth dynamics for understanding inequality. Piketty (2015b) clarifies how $R - G$ works not as a direct determinant of inequality but instead as

TABLE 1 Simulating Wealth Inequality Dynamics

	Initial	Long-run	
		Scenario A	Scenario B
Gini—baseline	0.70	0.75	0.99
(% change)		(7%)	(41%)
Top 1% share—baseline	0.20	0.24	0.94
(% change)		(20%)	(370%)
Gini—constant saving rate	0.70	0.47	0.99
(% change)		(−33%)	(41%)
Top 1% share—constant saving rate	0.20	0.13	0.99
(% change)		(−35%)	(365%)
Gini—no imputed rents	0.71	0.64	0.99
(% change)		(−10%)	(39%)
Top 1% share—no imputed rents	0.21	0.18	1
(% change)		(−14%)	(376%)

Notes: Scenario A applies average growth rates to all percentiles (G and R); scenario B applies percentile-specific growth rates ($g = g_p$ and $r = r_p$). Gini coefficients across net wealth percentiles are calculated at time $t = 1$ (on average for the years 2012–2018) and time $t = 150$ for net wealth. Percentage changes in parentheses. We show results at time $t = 150$ in order to avoid considering transitory adjustment effects of the simulation. For simplicity, we assume no wealth mobility. In the calculation of Gini coefficients, negative values are set to zero. See Figure A1 in the Appendix for the evolution over time of Gini coefficients for the different baseline scenarios. Notice that considering a longer time span does not alter the results. In the scenario with constant saving rate, $s_p = 7\%$. The code to fully replicate the simulation exercise is available publicly on Open Science Framework (https://osf.io/4s8c5, accessed 3 February 2023).

an amplifier of other kinds of shocks, increasing inequality in the steady state and making disparities more persistent. Our findings suggest that the heterogeneity of $r - g$ across the distribution should be added to the list of determinants of increasing wealth inequality.

To what extent are these results robust to relaxing the assumption of no wealth mobility? The work of Gomez (2022) proposes a novel accounting framework to decompose the wealth share of a top percentile (say the top 1%) as a sum of three components: the *within*, *between* and *demography* terms. The *within* term represents the average wealth growth of individuals within the top percentile, relative to the rest of the distribution, while the *between* term measures the degree of mobility by accounting for individuals entering and exiting the top percentile. Gomez (2022) shows empirically, using the Forbes 400 list, that although the *within* component is the biggest (3% against a *between* component of 2.5%), the wealth share of the top percentile of the wealth distribution would grow much less without taking the *between* term (the proxy of wealth mobility) into consideration.

In our context, since the simulation assumes a percentile-specific saving rate (as an approximation of individual-specific saving rates) and percentile-level variation in income and return behaviours, we indeed abstract from considering the potential role of wealth mobility. A positive degree of wealth mobility (the *between* component) would influence the results of the simulation exercise, hence we can potentially overestimate the magnitude of the impact on wealth inequality and concentration deriving from heterogeneity in $r - g$. However, recall that the main take-away of our paper is the relevance of considering $r - g$ as a distribution (as in scenario B), rather than as a scalar (as in scenario A). Since the issue of mobility is a relevant critique to all inequality measures computed in a repeated cross-sectional setting rather than in a dynamic panel setting, the same will happen for $r - g$ considered as a scalar (scenario A). In other words, although the magnitudes could be influenced, a high degree of mobility would not offset the relevance of considering $r - g$ as a distribution, rather than as a scalar. In the third subsection of this section, we analyse the role of mobility by considering age as a determinant of the steepness of wealth accumulation paths across the lifecycle, and therefore a predictor of wealth mobility.

5.2 | Simulating an alternative wealth accumulation equation

In this subsection, we show that results of the simulation in the previous subsection are robust to modifying the wealth accumulation equation according to the models presented in Benhabib and Bisin (2018), Benhabib *et al.* (2017) and Gabaix *et al.* (2016). To this end, Table 2 presents results when we assume that wealth evolves according to the following law of motion:

$$W_{p,t} = W_{p,t-1} + r_p W_{p,t-1} + s_p Y^L_{p,t}, \tag{11}$$

where $Y^L_{p,t} = (1+g)\, Y^L_{p,t-1}$. In this case, capital incomes ($r_p W_{p,t-1}$) enter directly in the wealth accumulation equation, and individuals save out of labour income ($s_p Y^L_{p,t}$). Results shown in Table 2 are qualitatively in line with those in Table 1.

Although the result of a decreasing Gini coefficient in scenario A might appear counterintuitive, this is mostly due to the interacting joint distribution of labour income and wealth in our data, which we use to initialize the simulation exercise. In particular, although the correlation between average labour income and net wealth over the period 2012–2018 is positive and high for most parts of the net wealth distribution, as expected, labour income and wealth happen to be negatively correlated for percentiles in the bottom 30% of the net wealth distribution.

TABLE 2 Simulating Wealth Inequality Dynamics—Alternative Accumulation Equation

		Long-run	
	Initial	Scenario A	Scenario B
Gini—baseline	0.70	0.52	0.99
(% change)		(−26%)	(41%)
Top 1% share—baseline	0.20	0.12	0.91
(% change)		(−40%)	(355%)
Gini—constant saving rate	0.70	0.45	0.99
(% change)		(−36%)	(41%)
Top 1% share—constant saving rate	0.20	0.13	0.93
(% change)		(−35%)	(365%)
Gini—no imputed rents	0.71	0.47	0.99
(% change)		(−34%)	(39%)
Top 1% share—no imputed rents	0.21	0.11	1
(% change)		(−48%)	(376%)
Gini—no joint distribution effect	0.70	0.74	0.99
(% change)		(6%)	(41%)
Top 1% share—no joint distribution effect	0.20	0.21	0.99
(% change)		(5%)	(395%)

Notes: Scenario A applies average growth rates to all percentiles (G and R); scenario B applies percentile-specific growth rates ($g = g_p$ and $r = r_p$). Gini coefficients across net wealth percentiles are calculated at time $t = 1$ (on average for the years 2012–2018) and time $t = 150$ for net wealth. Percentage changes in parentheses. We show results at time $t = 150$ in order to avoid considering transitory adjustment effects of the simulation. For simplicity, we assume no wealth mobility. In the calculation of Gini coefficients, negative values are set to zero. See Figure A2 in the Appendix for the evolution over time of Gini coefficients for the different baseline scenarios. Notice that considering a longer time span does not alter the results. In the scenario with constant saving rate, $s_p = 7\%$. The code to fully replicate the simulation exercise is available publicly on Open Science Framework (https://osf.io/thsm7, accessed 3 February 2023).

This is because individuals in the bottom portion of the net wealth distribution often have high levels of indebtedness that they sustain through high levels of income (as shown in panel B of Figure 1). When considering a single homogeneous $R-G$, the effect of saving out of increased labour income for the bottom 30% predominates over the effect of increased capital income for the wealthy rich due to higher returns, resulting therefore in an overall reduction of wealth inequality. Under scenario B instead, the effect of return heterogeneity implies higher rates of return on wealth for the wealthy rich, which overcome the counteracting saving effect at the bottom of the net wealth distribution. For clarity, we therefore conducted an additional exercise in which we assume an initial labour income level that is proportional to wealth (hence avoiding joint distributional effects). This yields a slight increase in both the Gini coefficient (6%) and the top 1% share (5%) for net wealth in scenario A. The gap between scenarios A and B is also reduced; however, it remains positive and significant.

5.3 | Persistent heterogeneity, scale dependence, or both?

To what extent is the main finding shown in Figure 5 caused by persistent heterogeneity in returns across the net wealth distribution, and to what extent is it instead determined by wealth scale effects? By persistent heterogeneity, we mean idiosyncrasies in returns, which may, for instance, be attributed to differences in risk preferences, or the ability to catch entrepreneurial opportunities. By scale dependence, we mean a positive effect of the scale of net wealth on returns. Guiso and Jappelli (2020) show that financial information leads to higher returns for investors, and since information is costly, wealthier individuals have a stronger incentive to invest in information. As a result, investment in information happens to be positively associated with returns to (especially financial) wealth.

The implications of the above question are decisive for the study of wealth inequality. As argued by Piketty (2014, p. 430): 'It is perfectly possible that wealthier people obtain higher average returns than less wealthy people … It is easy to see that such a mechanism can automatically lead to a radical divergence in the distribution of capital.' To investigate the relative importance of scale effects, we follow both Fagereng *et al.* (2020) and Gabaix *et al.* (2016), and estimate the following baseline two-way fixed-effects model:

$$(r-g)_{i,t} = \theta \; D(w_{i,t}) + \omega_i + f_t + \phi_i + \varepsilon_{i,t}, \tag{12}$$

where $(r-g)_{i,t}$ denotes the micro $r-g$ for individual i at time t, $D(w_{p,t})$ represents the deciles of the net wealth distribution (capturing scale effects), ω_i and f_t are individual (capturing persistent heterogeneity) and time fixed effects (capturing time-dependent covariation in $r-g$ and net wealth), respectively, ϕ_i is age (standardized), and $\varepsilon_{i,t}$ is the error term. In other words, the coefficient θ represents the scale dependence parameter. Since no other controls are included, this parameter includes direct and indirect scale dependence effects. We run the regression on a random 15% of the total population sample, namely 642,959 individuals. Table 3 shows the results.

Results from Table 3 imply that once individual time fixed effects and age are accounted for, jumping from one decile to another of the net wealth distribution will imply on average a higher $r-g$ of 0.029 percentage points. How do we make sense of this result? We know from our main evidence in Figure 5 that a move from the lowest to the highest decile of the net wealth distribution would imply an increase in $r-g$ by approximately 10 percentage points, hence roughly 1 percentage point per decile. Since the scale parameter implies that each decile shift leads to an average increase in $r-g$ of 0.029 percentage points, jumping from the lowest to the highest decile (8 times θ) corresponds on average to a higher $r-g$ of approximately 0.23712 percentage points. This amounts to approximately 2.3% of the entire variation in $r-g$ (of approximately

TABLE 3 Explaining Heterogeneity in the Distribution of $r - g$

	$r - g$ (1)	$r - g$ (2)	$r - g$ (3)
$\theta(decile)$	0.05007***	0.05219***	0.02964***
	(13.8315)	(14.1552)	(8.07869)
Individual-level fixed effects	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes
Age (standardized)	No	No	Yes
Observations (individuals * year)	3,778,665	3,778,665	3,778,665
Individuals	642,959	642,959	642,959

Notes: The table shows regression estimates of the micro $r - g$ as in the model specification given by equation (5). 'Yes' implies that the regressor is included; 'No' implies that it is not. Due to the computationally demanding magnitude of the panel comprising the whole population with 4,286,390 individuals, we run the regression on a random 15% of the total sample, namely 642,959 individuals. Total observations are given by the amount of individuals multiplied by the number of years (7), minus missing observations. The code to fully replicate this table using register data on microdata.no (upon being granted access to the interface) is available publicly on Open Science Framework at https://osf.io/mu9yx (accessed 30 January 2023). t-statistics are given in parentheses.
*, **, *** indicate statistical significance at the 10%, 5%, 1% level, respectively.

10 percentage points) and can be deemed negligible, leading us to conclude that scale dependence does not appear to be a key determinant of the increase in $r - g$ across the wealth distribution, in the context of our study.

Could a positive degree of wealth mobility invalidate these results, and how do we control for that within a cross-sectional framework? Aaberge and Mogstad (2015) document that cross-sectional estimates of income inequality are likely to be sensitive to the age composition of the sample. As a consequence of that, differences in age composition matter when comparing cross-sectional estimates of income (or wealth) inequality across countries or time. Based on this evidence, in model specification (12), we consider age as a determinant of the steepness of wealth accumulation paths across the lifecycle, and therefore a predictor of wealth mobility. Hence the fact that age has little explanatory power across percentiles in explaining $r - g$ is in our view an indication that wealth mobility does not play a decisive role in explaining our results.

5.4 | Do the types of wealth and rate of return correlate?

Not all wealth owners are equal, and the type of wealth (real or financial) substantially impacts rates of return and capital incomes, and in turn $r - g$. Do we gain additional insights by separating the types of wealth owners? We compute for all years the shares of housing (including the estimated market value of first and secondary dwellings) and financial wealth on personal gross wealth, with individuals ranked by their position in the net wealth distribution.

From Figure 7, which shows the percentile share of housing in panel (a) and of financial wealth in panel (b), it is clear how housing represents the main wealth component for the middle class 50–90%, since it stands for approximately 75–80% of their gross wealth. Focusing on the top 10%, the picture changes slightly. Housing remains the biggest component of gross wealth for the 90th–99th percentiles, although with a lower share before it drops to approximately 20% of total gross wealth for the top 1%.[13]

Next, we specify a baseline two-way fixed-effects model to synthesize the information on types of wealth (real and financial) and their relevance for $r - g$:

$$(r - g)_{i,t} = \omega_i + f_t + \rho_{i,t} + \mu_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t}, \tag{13}$$

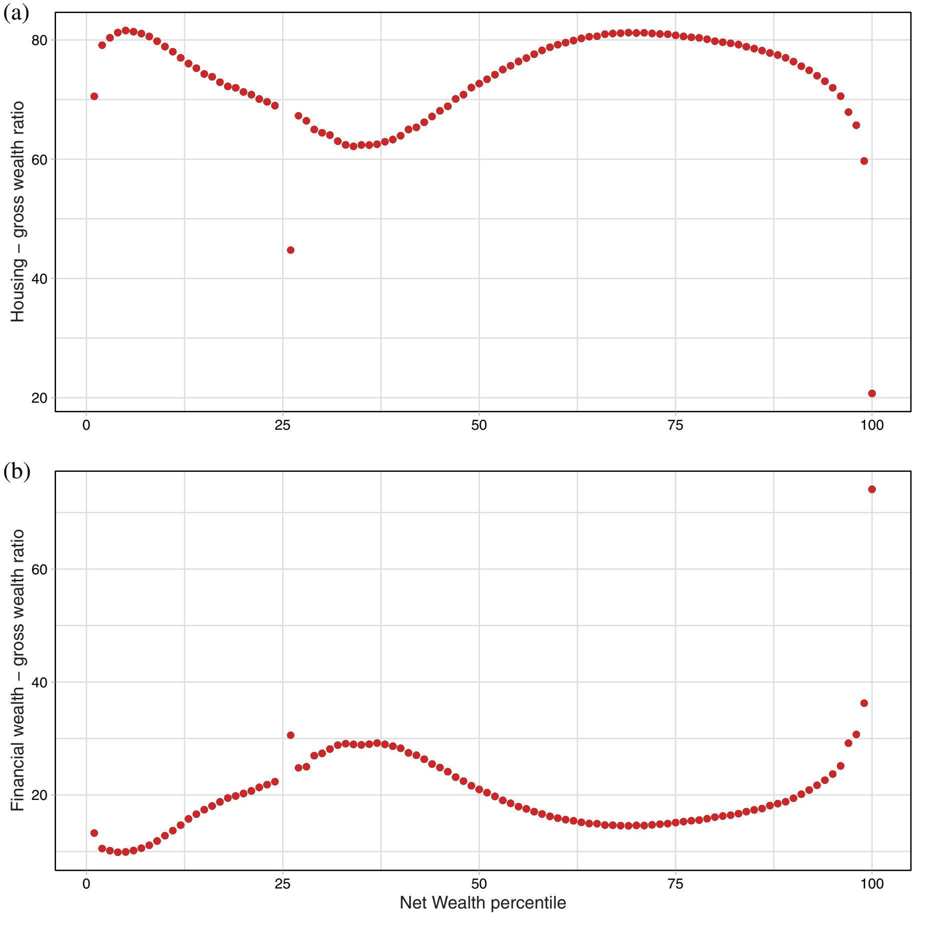

FIGURE 7 Financial wealth and housing shares of gross wealth. *Notes*: This figure shows the shares of housing (including estimated market value of first and secondary dwellings) and financial wealth on personal gross wealth, with individuals ranked by their position in the net wealth distribution. Averages across the 2012–2018 time period.

where $(r-g)_{i,t}$ denotes the micro $r-g$ for individual i at time t. Here, ω_i and f_t are the individual and time fixed effects, respectively, $\rho_{i,t}$ is the lagged share of financial wealth on gross wealth for each percentile, $\mu_{i,t} = 1 - \rho_{i,t}$ is the lagged share of real capital, and $\varepsilon_{i,t}$ is the error term.

Results are shown in Table 4. In model specifications (1) and (2), the lagged share of financial wealth is included as the main regressor, in addition to control variables such as individual and time fixed effects. A 1 percentage point increase in the lagged share of financial wealth leads to a 3.97% increase in $r-g$ (column (2)), implying that the type of wealth matters and that an increasing share of financial wealth leads to higher $r-g$ for large owners of financial wealth. In model specifications (3) and (4), we include the lagged share of real capital as the main regressor, in addition to control variables such as individual and time fixed effects. As expected, a 1 percentage point higher share of real capital is expected to lead to a 3.97% lower $r-g$ (column (4)), opposite to what we observed for financial wealth. All in all, this evidence indicates that if the policymaker's intention is to curb wealth inequality, then reducing dispersion in $r-g$ by incentivizing the wealthy poor to own higher shares of financial wealth within their gross wealth levels would be a viable policy option.

TABLE 4 Explaining Variation in $r - g$ in Relation to Type of Wealth Owners

	$r - g$ (1)	$r - g$ (2)	$r - g$ (3)	$r - g$ (4)
Lagged financial capital (%)	3.94316***	3.9789***		
	(104.01)	(105.216)		
Lagged real capital (%)			−3.94316***	−3.9789***
			(−104.01)	(−105.216)
Percentile fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	No	Yes
Observations (individuals * year)	3,778,665	3,778,665	3,778,665	3,778,665
Individuals	642,959	642,959	642,959	642,959

Notes: The table shows regression estimates of the micro $r - g$ as in the model specification given by equation (6). All regressions are computed on 1-year lagged wealth variables (shares of gross wealth). 'Yes' implies that the regressor is included; 'No' implies that it is not. Due to the computationally demanding magnitude of the panel comprising the whole population with 4,286,390 individuals, we run the regression on a random 15% of the total sample, namely 642,959 individuals. Total observations are given by the amount of individuals multiplied by the number of years (7), minus missing observations. The code to fully replicate this table using register data on microdata.no (upon being granted access to the interface) is available publicly on Open Science Framework at https://osf.io/bre8g (accessed 30 January 2023). t-statistics are given in parentheses.
*, **, *** indicate statistical significance at the 10%, 5%, 1% level, respectively.

6 | CONCLUDING REMARKS

The main take-away of this paper is that $r - g$ should be considered as a distribution, and not as a scalar. To provide the grounds for this claim, the paper utilizes individual-level Norwegian tax records on income and wealth, analysing for which portions of net wealth distribution, returns to wealth happen to be higher (or lower) than growth rates of income. The implication is that the full distribution of $r - g$, which we show to be positively associated with position in the net wealth distribution, delivers higher predictive power for the study of the dynamics of income and wealth inequality than simply focusing on the aggregate $R - G$.

We show that for the top 40% of the distribution, the aggregate $R - G$ underestimates its micro counterpart $r - g$, while the opposite is true for the bottom 60%. We show as well that for the bottom 50% of the population, it is indeed the case that $r < g$. We also investigate the determinants of this covariation between $r - g$ and position in the wealth distribution. We show that after controlling for persistent heterogeneity, only a negligible fraction of the entire variation in $r - g$ (when moving up from the bottom decile to the top decile of the net wealth distribution) can be explained by scale dependence. This leaves open the debate regarding the relative importance of scale effects in determining rates of return on wealth. We also analyse the correlation between returns and type of wealth, showing that the role of financial wealth is paramount in raising the level of returns, and in turn of $r - g$. This evidence indicates that allowing the wealth-poor to increasingly participate to the ownership of financial wealth would be a valid policy to curb disparities in returns, and in turn reduce wealth inequality in the longer run.

In our view, this empirical exercise confirms the relevance of taking into account substantial heterogeneity when modelling the distribution of wealth in relation to macroeconomic phenomena. We also believe that the results of this research enhance our understanding of the relevance of the *inequality* $r > g$, for the study of wealth inequality. That said, our work has left aside important aspects such as the role of public wealth, and partially of retained earnings (undistributed profits kept within firms, which are included only insofar as they are reported to the tax authorities). If anything, results from the scant empirical evidence on the latter allow us to speculate that allocating the remaining portion of undistributed profits would imply even stronger heterogeneity of $r - g$ across the wealth distribution, reinforcing this work's main message.

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The views expressed herein are those of the authors and do not necessarily reflect those of our institutions. All errors are our own.

NOTES

[1] Data are retrieved from https://microdata.no, an online portal administered by Statistics Norway. In order to ensure reproducibility of our results, we have made publicly available on Open Science Framework (https://osf.io/nct45) the codes to replicate the descriptive results, figures and econometric analyses of the paper.

[2] Fagereng *et al.* (2020) compute unrealized capital gains on housing as the yearly change in housing wealth after subtracting transactions. We abstract from transactions due to data availability.

[3] Table 10315: Property account for households 2010–2021, from https://www.ssb.no/en/statbank/table/10315 (accessed 29 January 2023).

[4] Statistics Norway Table 09114: Measures of income dispersion. Household equivalent income (EU-scale) between persons (M) (UD) 2004–2018.

[5] Robustness checks on trimming are provided in the third subsection of the Appendix. Volatility in r, the rate of return on net worth, is especially high for individuals exhibiting low levels of gross wealth, while high volatility in growth rates of income is due mostly to capital gains on housing wealth. In any case, our corrections are conservative, and if anything, they reduce the extent of heterogeneity of r and g across the net wealth distribution.

[6] Piketty's $r > g$ has been conceptualized by defining g as the growth rate of income, hence incorporating both per capita income growth rate and population growth rate. For advanced economies with null or very low population growth, Piketty (2015b) adds that the role of population growth becomes indeed of second-order importance.

[7] Notice here that this definition, consistently with the aggregate G in equation (3), also includes the time-invariant population growth 1%.

[8] For a comparison, Fagereng *et al.* (2019) show that between 2012 and 2015, Norway's aggregate wealth–income ratio (they label this series as 'No saving by holding') ranged from around 450% to around 480%.

[9] Each percentile is initialized with the average percentile-specific value over the period 2012–2018 for the different variables considered in this exercise.

[10] In other words, we take into account that a part of income (stemming from both capital and other sources), i.e. $(1 - s_p)\,Y_{p,t}$, is consumed.

[11] Notice that this is a simplifying assumption, as for the bottom 20%, saving rates are actually U-shaped. Nevertheless, this does not significantly impact results, as including a U-shaped saving rate at the very bottom yields a Gini coefficient converging to 0.78 instead of 0.75 in baseline scenario A, but an identical Gini in baseline scenario B (see text). Values are retrieved from the most recent version of Fagereng *et al.* (2019) at https://benjaminmoll.com/wp-content/uploads/2019/07/SBWD.pdf (accessed 29 January 2023).

[12] Here, we assume that labour income grows at rate g with the aim of rendering our framework more comparable to the model in Mankiw's critique of Piketty's arguments (Mankiw 2015), in which g is referred to as labour-augmenting technical progress. Letting income grow at g does not alter the general conclusions. Results may be provided on request.

[13] This is in line with evidence from other countries. For example, Acciari *et al.* (2021, p. 10) find that for Italy, 'the wealth shares of all groups above the 90th percentile are mostly driven by the dynamics of non-housing assets'.

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APPENDIX A

Descriptive statistics

TABLE A1 Descriptive Statistics of the Baseline Sample

Variable	Category	Observations	Mean	S.D.	Min	Max
Personal gross wealth (*gw*)	2010	3,672,154	1,463,380.1028	1,685,698.0736	0	9,329,716
	2011	3,736,564	1,554,668.584	1,788,062.487	0	9,829,390
	2012	3,796,370	1,683,743.0032	1,907,787.5646	0	10,462,519
	2013	3,850,558	1,757,966.1676	2,011,619.0821	0	11,067,254
	2014	3,904,534	1,814,654.1231	2,066,818.6761	0	11,455,698.33
	2015	3,951,412	1,942,130.2156	2,217,501.5086	0	12,424,534
	2016	3,995,151	2,079,815.851	2,399,362.3057	0	13,564,935
	2017	4,061,631	2,206,908.234	2,592,048.4519	0	14,868,726.56
	2018	4,126,767	2,234,013.351	2,641,582.311	0	15,340,798
	2010–2018		35,095,141			
Private debt (*d*)	2010	3,672,154	572,006.9409	887,600.6338	0	4,796,267
	2011	3,736,564	604,197.2627	938,542.5002	0	5,038,880
	2012	3,796,370	640,141.8714	992,279.3503	0	5,301,895
	2013	3,850,558	675,494.5575	1,046,485.1423	0	5,601,334
	2014	3,904,534	705,418.2386	1,090,841.0443	0	5,817,836
	2015	3,951,412	738,784.8513	1,143,644.2329	0	6,070,201
	2016	3,995,151	774,263.3705	1,201,549.8505	0	6,367,489
	2017	4,061,631	807,733.4229	1,260,241.406	0	6,684,241
	2018	4,126,767	837,090.6793	1,309,206.2736	0	6,941,879
	2010–2018		35,095,141			

(Continues)

TABLE A1 (Continued)

Variable	Category	Observations	Mean	S.D.	Min	Max
Personal net wealth (w)	2010	3,672,154	891,373.1619	1,581,126.2314	−4,796,267	9,329,716
	2011	3,736,564	950,471.3213	1,670,687.3286	−5,038,880	9,829,390
	2012	3,796,370	1,043,601.1318	1,768,568.4121	−5,301,895	10,462,519
	2013	3,850,558	1,082,471.61	1,871,589.4863	−5,601,334	11,067,254
	2014	3,904,534	1,109,235.8845	1,926,933.7456	−5,817,836	11,455,698.33
	2015	3,951,412	1,203,345.3643	2,065,344.3123	−6,070,201	12,424,534
	2016	3,995,151	1,305,515.2237	2,231,434.3546	−6,367,489	13,564,935
	2017	4,061,631	1,399,136.5817	2,402,849.0841	−6,684,241	14,868,726.56
	2018	4,126,767	1,396,883.9111	2,452,349.2445	−6,941,879	15,340,798
	2010–2018		35,095,141			
Capital income (k)	2010	3,672,154	10,388.7938	36,130.7456	−6255	287,378
	2011	3,736,564	11,671.6094	39,172.2868	−12,011	307,958
	2012	3,796,370	12,574.3758	41,266.2958	−3030	324,819
	2013	3,850,558	14,212.711	46,434.3561	0	364,900
	2014	3,904,534	15,133.9046	50,644.2364	−4918	400,050
	2015	3,951,412	15,467.0957	62,335.6454	−14,240	510,809
	2016	3,995,151	12,690.2313	54,444.6483	−16,499	446,348
	2017	4,061,631	13,521.0656	57,585.0475	−16,063	473,962
	2018	4,126,767	13,531.2799	56,577.9826	−6494	468,565
	2010–2018		35,095,141			
Total fiscal income (y)	2010	3,672,154	370,486.8579	241,542.426	0	1,441,504
	2011	3,736,564	387,346.7956	255,816.7936	0	1,525,017
	2012	3,796,370	403,894.1623	268,705.8449	0	1,593,909
	2013	3,850,558	419,618.4645	281,579.7698	0	1,665,686
	2014	3,904,534	432,801.0258	292,761.3459	0	1,737,556
	2015	3,951,412	445,533.6917	307,390.4366	0	1,888,036
	2016	3,995,151	449,121.896	302,836.0827	0	1,821,027
	2017	4,061,631	454,857.311	311,373.0565	0	1,859,382
	2018	4,126,767	463,823.6129	323,328.2209	0	1,913,067
	2010–2018		35,095,141			

Notes: This table presents the summary statistics of our baseline sample. Our sample is constructed by considering the entire population of residents of age 20 years and above, between 2010 and 2018. All variables are pre-tax and are considered at the last day of the year. All numbers are given in Norwegian kroner.

Simulation analysis

Figure A1 displays the evolution over time of the Gini coefficient for net wealth in our simulation (scenarios A and B) when calibrating on our average (over the period 2012–2018) percentile-level data. Results are robust when simulating the alternative wealth accumulation equation in the second subsection of Section 5 (see Figure A2). Indeed, allowing for heterogeneity in r and g (scenario B) entails higher long-run wealth inequality with respect to considering homogeneous r and g (scenario A).

Alternative trimming strategies

In Figure A3, we have restricted the sample according to the following rules. First, we leave out percentiles 24–27, as these have close to zero net and gross wealth. Second, we leave out income growth rates that are greater than 0.41 (four observations), as we suspect that these large numbers are driven by our imputation procedure for housing capital gains. This trimming strategy excludes 5% of the total sample.

In Figure A4, we have restricted the sample according to the following rules. For percentiles with wealth close to zero, we exclude observations for which rates of return are extreme (values larger than 100%), as we suspect that these are artificially inflated by low denominators. Furthermore, we exclude extreme values for income growth rates, as these are due to our imputation procedure for housing capital gains. This trimming strategy excludes 2% of the total sample.

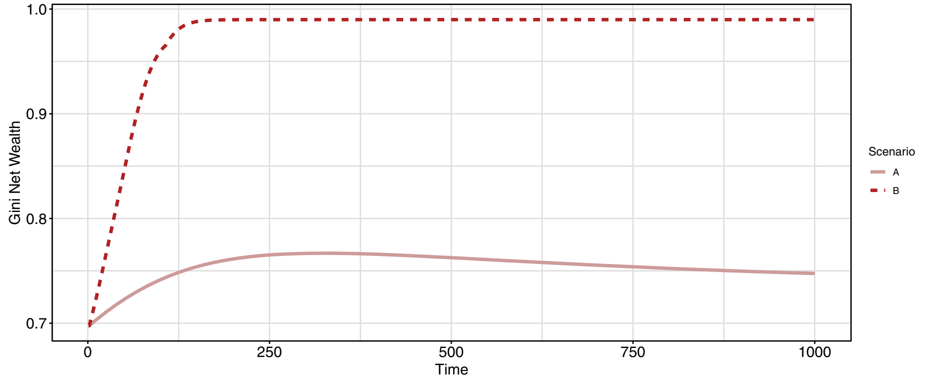

FIGURE A1 Simulated Gini coefficient of net wealth.

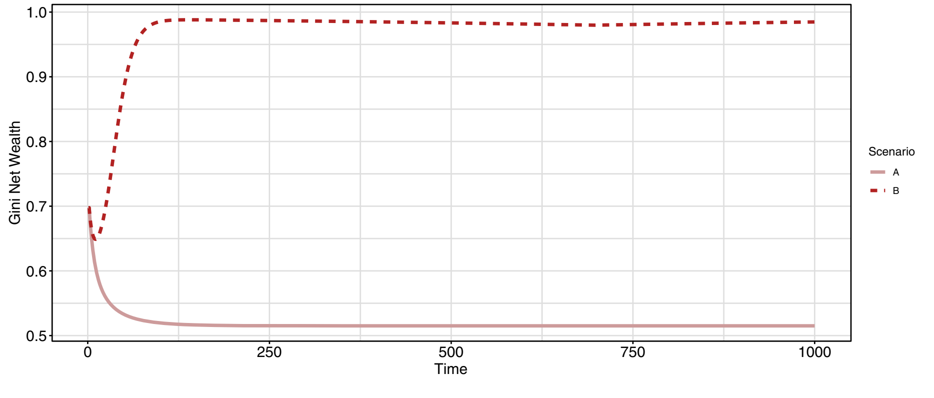

FIGURE A2 Simulated Gini coefficient of net wealth—alternative wealth equation.

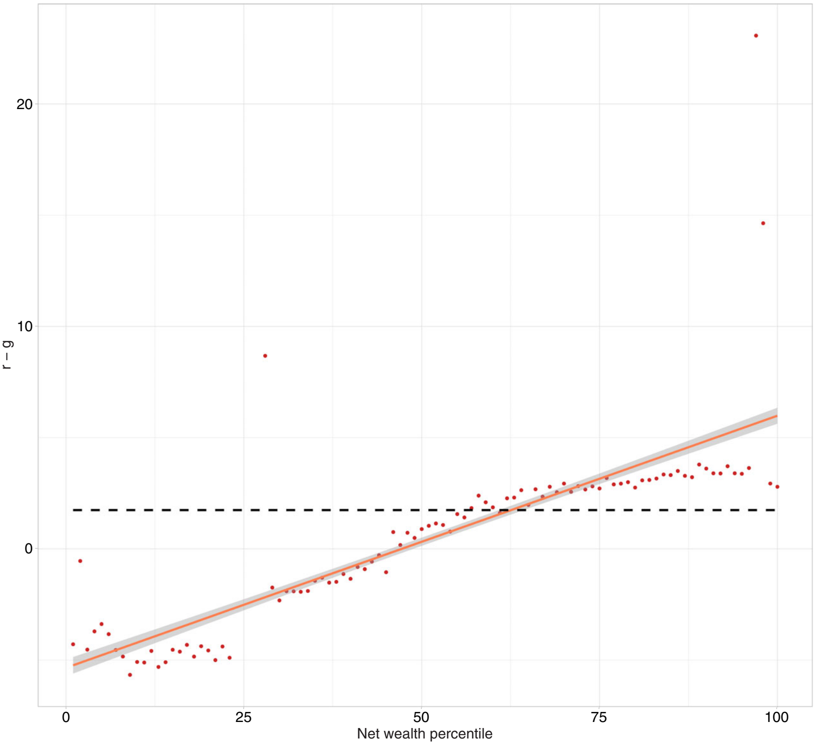

FIGURE A3 $r - g$ with alternative trimming procedure (1).

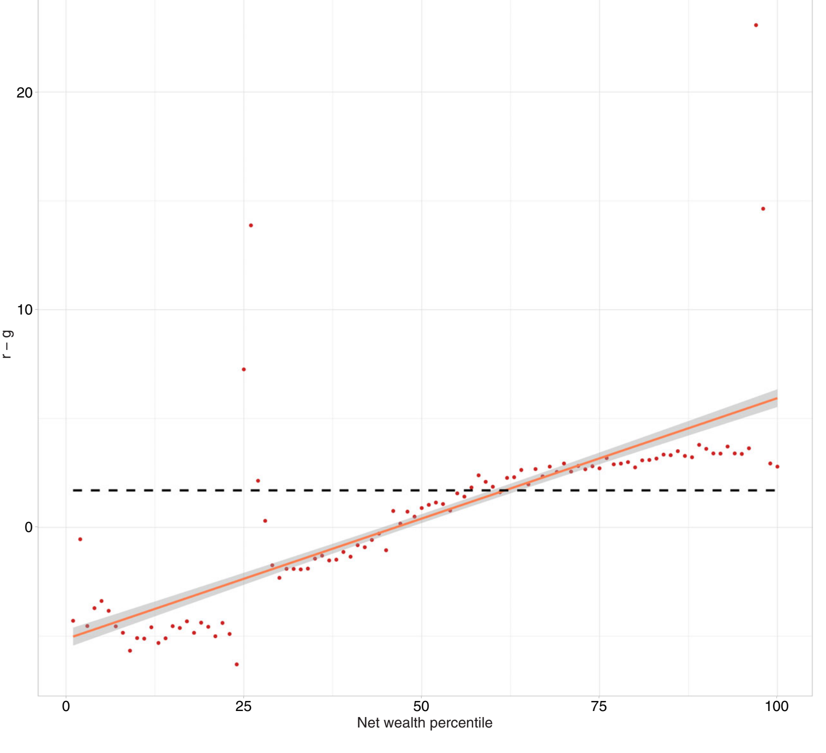

FIGURE A4 $r - g$ with alternative trimming procedure (2).

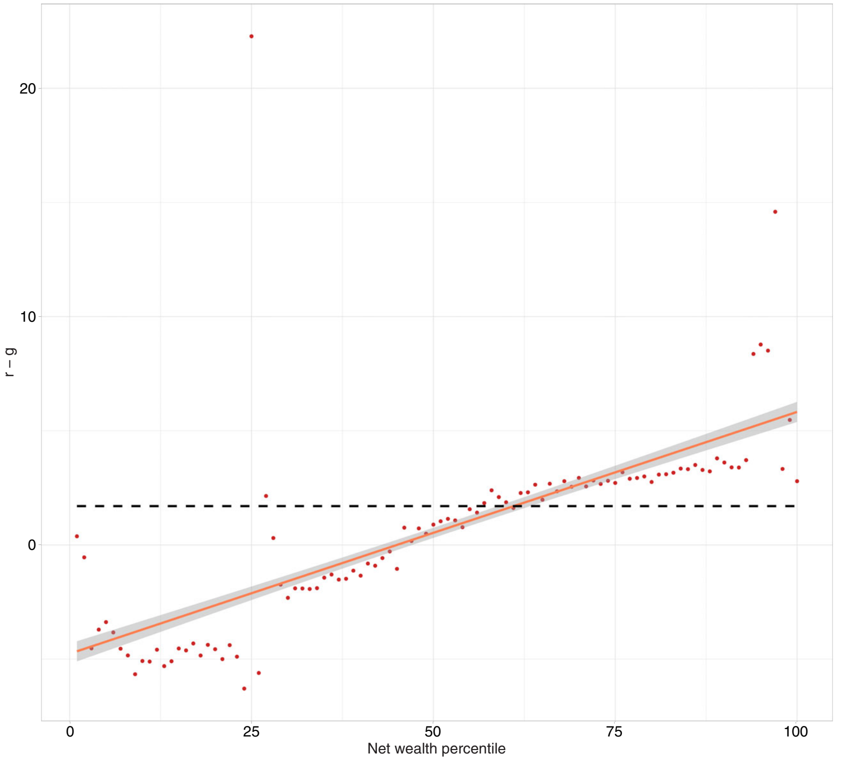

FIGURE A5 $r - g$ with alternative trimming procedure (3).

Finally, in Figure A5, we trim 2% of the tails of the variable $r - g$.

Our main finding on the shape of $r - g$ along the net wealth distribution is generally confirmed, even if, in the three cases explained in this subsection, further heterogeneity and some outliers are present with respect to our baseline sample.