

Accounting for Wealth Concentration in the United States

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Abstract

We assess the empirical relevance of different macroeconomic modeling approaches to wealth concentration, using the joint distribution of earnings, capital income and net worth in combination with an OLG model of household heterogeneity. We find large earnings disparities to be the primary source of US wealth concentration. This reflects the fact that labor income, from salaries but also from entrepreneurship, is a major income source for top income and wealth groups in the data. Bequests and differences in rates of return on capital together explain about half the holdings of the wealthiest of households.

JEL Codes: D31, D33, E21

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1 Introduction

Net worth, the balance of a household's assets and liabilities, is highly concentrated in the US, with the wealthiest 1% holding over a third of total wealth. Economists have proposed a set of explanations for this, highlighting factors such as labor income heterogeneity; capital return heterogeneity; entrepreneurial activity, which combines heterogeneity in labor and capital incomes; or bequests. These explanations differ in their depictions of who the wealthy are and how they become wealthy, yielding conflicting perspectives on economic policy.¹ Regrettably, a direct empirical assessment of how important labor and capital income are for building fortunes in the US has proven elusive due to the lack of longitudinal data on finances of high-wealth households.

In this paper, we assess the relevance of different modeling approaches by exploiting their diverging predictions for the income composition of top income and wealth groups. If concentration is driven by asset return differences or bequests, these groups should rely heavily on capital income. In contrast, prominent labor income should point to earnings heterogeneity as a key driver of wealth concentration.

Data from administrative tax records show a substantial labor income component for high-income households (Piketty et al., 2018). We reach a similar conclusion using data from the Survey of Consumer Finances (SCF). Earnings account for almost a half to two thirds of total income for the top 1% of incomes, depending on the treatment of capital gains and proprietors' income. Households outside the top groups rely almost exclusively on labor income. These suggest an indispensable role for earnings in shaping the wealth distribution.

The lower labor income shares among the highest income and wealth groups nonetheless reflect the relative importance of capital income for these groups. Our analysis indicates, however, that the low shares among the wealthiest mainly reflect their larger asset stocks rather than higher returns. By contrast, we estimate sizable return differences across income groups even after accounting for their wealth.

The effect of these differences on wealth concentration depends on fluctuations in income and asset returns over a lifetime. However, cross-sectional data alone cannot reveal how such dynamics impact wealth accumulation. To discipline these dynamics, we employ a life-cycle model of wealth formation calibrated to match the *joint* distributions of earnings, income,

¹For example, Kindermann and Krueger (2022) prescribe an optimal top marginal tax rate of 90% using a model of labor income risk, whereas Brüggemann (2021) calls for a 60% rate based on a model of entrepreneurship. Guvenen et al. (2023) argue that wealth taxes may bring efficiency gains in models with rate of return heterogeneity. Similarly, Hubmer et al. (2020) attribute much of the rise in wealth concentration to top income tax cuts, whereas Kaymak and Poschke (2016) attribute it to widening earnings dispersion.

and wealth in the data, in contrast to common macro approaches that focus solely on marginal distributions.

The model incorporates key savings motives like precautionary behavior, retirement planning, and bequests. When combined with empirical income and wealth distributions, the calibrated model yields realistic earnings risk, variation of asset returns with income and wealth, and life-cycle profiles of earnings, income and wealth.

Conducting a series of counterfactual experiments to assess each component's contribution to wealth concentration, we find earnings heterogeneity to be the primary driver of top wealth shares, directly explaining about half of wealth concentration on average, regardless of the presence of other mechanisms in the model.

Differences in bequests and asset returns together explain the remainder of wealth concentration. Individually, return heterogeneity mostly impacts the top 0.1% wealth share, while bequest inequality mostly affects the Gini coefficient of wealth. The two mechanisms amplify each other, especially in terms of their effect on the top wealth shares. The marginal effect of each is much smaller when the other mechanism is absent.

Overall, our results emphasize theories based on earnings concentration. The findings reflect the significance of labor income among top groups and are robust to measurement concerns and the exclusion of entrepreneurs. In contrast, we show that explanations relying solely on returns or bequests severely underestimate the concentration of earnings in the economy, while dramatically overstating capital shares among top income and wealth groups.

In the next section, we give a brief overview of the related literature. In Section 3 we summarize the empirical distributions of earnings, income and wealth and document the rates of return by income and wealth implied by the factor composition of income. We present the model in Section 4, calibrate it in Section 5 and discuss the benchmark economy in Section 6. Section 7 analyzes the relative roles of rate of return heterogeneity, labor income risk and bequests in wealth concentration. Section 8 illustrates the sources of identification and discusses the robustness of our results to model specification and measurement. Section 9 provides a discussion of our findings vis-à-vis the literature.

2 Macroeconomics of the Wealth Distribution

The foundations of modern macroeconomic analysis of the wealth distribution are laid out in early work by Imrohoroglu (1989), Huggett (1993) and Aiyagari (1994). In this setting, dis-

persion in asset holdings emerges from households' motives to accumulate assets in order to insure themselves against earnings fluctuations. While early models focused on implications of earnings risk for macro outcomes like aggregate savings or the interest rate, it was noted that income differences observed in household surveys were not large enough to generate a highly skewed wealth distribution. The subsequent literature aimed to enhance the model for applications to questions related to wealth inequality. The macro literature on the wealth distribution now is vast, with applications to various economic questions. In our discussion here, we focus on the main modeling extensions.²

The main shortcoming in the original model was that wealthy households cared little about earnings risk and therefore limited their savings once their wealth was sufficiently high. The first modeling extensions that helped maintain continuing wealth accumulation, and thereby generate a more skewed wealth distribution, involved introducing differences in savings motives or rates of return on assets. This was achieved by explicitly introducing heterogeneity in preferences for saving (Krusell and Smith, 1998), in rates of return on assets (Benhabib et al., 2011; Gabaix et al., 2016; Nirei and Aoki, 2016; Cao and Luo, 2017), as well as bequest motives that are increasing in wealth (De Nardi, 2004). Benhabib et al. (2011) show analytically that idiosyncratic capital income risk can generate a Pareto tailed wealth distribution with a realistic tail index. Capital income risk is essential to a fat-tailed wealth distribution in some versions of the incomplete markets model, but is not generally necessary, e.g., if agents have finite lives (Jones, 2015; Stachurski and Toda, 2019; Sargent et al., 2021).

Benhabib et al. (2019), Hubmer et al. (2020) and Cao and Luo (2017) provide quantitative assessments of the contribution of rate of return heterogeneity to wealth concentration. The common element among these models is that the main source of differences in wealth accumulation is capital income. High wealth concentration emerges because wealthy households enjoy higher rates of return on their assets and have higher saving rates. As a consequence, capital income is essential to top income and wealth groups.

A second strand of the literature focused on better measurement of earnings. Household surveys typically provide an incomplete picture of the distribution of earnings and associated risks due to censoring of earnings above a certain level or limited sampling of high-earning households. Castañeda et al. (2003) were the first to show that the standard incomplete markets model can indeed generate a highly skewed wealth distribution if the earnings process is calibrated accordingly. This however required unrealistically high earnings levels

²See De Nardi and Fella (2017) for a more detailed review of the macro literature on wealth inequality.

for top income groups. Subsequent work refined this approach, using the recent progress in measurement of top earnings levels based on administrative data to discipline the extent of earnings dispersion in the model (Kindermann and Krueger, 2022; Kaymak and Poschke, 2016). The economic mechanism here is that households that temporarily have very high earnings face lower future earnings (be it because of retirement or the vagaries of a top-level career), and therefore have a very strong saving motive. The explicit consideration of very high earnings levels is a key ingredient in these models, where the main source of wealth concentration consists of differences in labor income and the associated saving behavior.

Another mechanism that can generate high wealth concentration is entrepreneurship, which combines elements from the two strands above, since profits reflect both the return on business investment and the value of entrepreneurial labor (Quadrini, 2000; Cagetti and De Nardi, 2006). Versions of these models without credit restrictions can be mapped into a model with earnings heterogeneity and a common return on assets because in equilibrium, the marginal rate of return on business capital is equalized across entrepreneurs (see Appendix A). Differences in business income net of the common return on capital, stemming from inframarginal returns to entrepreneurial skill, are then attributable entirely to labor. This interpretation is in line with recent work, which finds that entrepreneurial income primarily reflects the entrepreneur's human capital (Smith et al., 2019; Bhandari and McGrattan, 2021). In versions with credit constraints, some entrepreneurs reap higher (marginal) rates of return on their investments if, or as long as, they are financially constrained (Buera, 2009; Moll, 2014). In such cases, differences in business income reflect differences in both the investment returns and the productivity of entrepreneurial labor. The accounting approach we adopt below, both in our empirical and in our quantitative analysis, is consistent with this view.

All these approaches substantially improved the ability of the standard incomplete markets model to generate a realistic wealth distribution for the US, offering economists several modeling options. The existing literature has operated with either a model with capital income risk, one with high earnings dispersion, or one with entrepreneurship. Yet, the relative roles of earnings and capital income risk in generating the observed wealth concentration are not well understood, in part due to a lack of data on the dispersion and persistence of rates of return on assets at the household level in the US.³ Our analysis fills this gap.

³Recent work by Fagereng et al. (2020) and Bach et al. (2020) provide empirical evidence for rate of return heterogeneity using panel data from Norway and Sweden, respectively.

3 Income, Earnings and Wealth in the US

In this section we summarize the distributions of earnings, income and wealth, and discuss the relative significance of capital and labor for top income and wealth groups. The primary sources of data are the 2001 to 2019 waves of the Survey of Consumer Finances (SCF), a triennial cross-sectional survey of households on their assets, income, and demographic characteristics. The SCF is particularly suitable for our analysis since it oversamples high-income households and is commonly used in the macro literature to study upper tails of the income and wealth distribution (e.g. [Kuhn et al., 2020](#)).

3.1 Data and definitions

Since the objective is to identify the importance of different modeling components, we adopt a market-based notion of income that is compatible with the models of wealth distribution mentioned above. Market income includes wage and salary income, business and farm income, interest and dividend income, private pension withdrawals and capital gains, whereas it excludes income from fiscal sources, such as transfer income or Social Security income.

We distinguish between labor and capital income. Labor income consists of wage and salary income, including any salary drawn from an actively managed business. The vast majority of households report these explicitly in the SCF. Among business owners, active shareholders of corporations are explicitly required by the IRS to report their salaries. But some business organizations, such as partnerships and sole proprietorships, are exempt from this requirement. As a result, about 9% of households report some business income but no salary income associated with the business. In such cases, we impute the labor and capital components of business income. We impute a labor component only if a household reports income from actively owned businesses, but does not report any wage income, or if the respondent or their spouse reports explicitly that they did not draw salary from their actively managed business. This procedure does not change the conclusions we draw from the empirical patterns below, reported with and without imputed salaries. For our baseline analysis, we include imputed wages in labor income and later present a version without imputed wages for robustness.

To determine capital's share of active business income, we assume capital's contribution is proportional to business equity held. Consequently, we regress active business income on equity value, controlling for the quantity and quality of the labor input. Specifically, we include the number of hours worked by household members who are actively involved in the

business as well as demographic characteristics of the head of household, such as gender, age and education, as control variables. The resulting coefficient on equity is 0.25 (s.e. 0.03), which we interpret as the capital income share.⁴ We thus allocate 75 percent of active business income to labor for those who do not report wage income from their business.

Despite the differences in methodology and data sources, our estimate of 75 percent is close to that of [Piketty et al. \(2018\)](#), who attribute 70 percent of pass-through income to labor. While ascertaining the labor share of income among entrepreneurs is inherently difficult, our estimates potentially underestimate the contribution of entrepreneurial labor, and, hence, we see them as conservative given our findings. First, empirical work that relies on administrative tax records and variations in ownership that are more exogenous in nature suggest much higher roles for entrepreneurial labor. [Smith et al. \(2019\)](#), for instance, find that profits of a business decline substantially upon the owner's demise. Consequently, they attribute 75 percent of business *profits* to human capital, in addition to the reported salaries. Similarly, [Bhandari and McGrattan \(2021\)](#) attribute three quarters of profits to "sweat equity," which is embodied in the entrepreneur. We maintain profits as part of the return on capital. Second, we do not question the explicitly reported salaries, although business owners have tax incentives to underreport wage income. Third, among those who do not report wage income, we only impute wages for the spouse and the respondent due to data limitations. If other members of the household also work for the business, their labor income is classified as part of the household's business income.

Capital's share of income excludes accrued (but not realized) capital gains since they are not observed. Including them would lower the overall labor share, but it is not clear ex ante how it would change the *relative* labor shares across income and wealth groups, the critical input to our quantitative analysis below. [Burman and Ricoy \(1997\)](#) find that higher income groups are overwhelmingly more likely to realize capital gains and realize a large fraction of their gains when they do. They explain this by differences in portfolio composition: since housing is the main component of wealth for lower income groups, the associated capital gains are realized much less frequently relative to financial assets, which are concentrated among top income groups. This suggests that ignoring accrued gains leads to larger differences in labor shares across income groups, and, thereby, in rates of return on capital. This is consistent with [Larrimore et al. \(2021\)](#), where, for the 2001-2016 period, the average share of the top 1 percent of income is 19.5 with accrued gains, whereas it is 20.6 with realized gains alone (see their Appendix Table 2). This suggests that realized gains are

⁴This is the share in *net* income, since depreciation expenses are deducted from the reported business income. The share in gross income can be found by adding the rate of depreciation.

Table 1: Cross-Sectional Distributions of Income, Earnings and Net Worth

Top percentile	0.1%	0.5%	1%	5%	10%	20%	40%	Gini
Net worth	0.13	0.26	0.35	0.62	0.74	0.86	0.96	0.84 [†]
Income	0.08	0.17	0.22	0.40	0.51	0.66	0.85	0.66
Earnings	0.06	0.12	0.17	0.33	0.46	0.63	0.85	0.64 ^{††}

[†] Includes negative values. The Gini coefficient with non-negative values is 0.81.

^{††} The Gini coefficient for households with a working-age head is 0.56.

Note.— Table shows the cumulative concentration shares for the top percentile groups. Income includes capital gains. Source: SCF 2001 – 2019.

more skewed than the total (realized and accrued) capital gains.⁵

3.2 Marginal and joint distributions

Table 1 shows the cross-sectional distributions of income, earnings and wealth. The distribution of net worth is far more skewed than the distributions of income and earnings: the Gini coefficient for net worth is 0.84, whereas it is 0.64 for earnings and 0.66 for income. This is driven by both the heavier concentration of wealth at the top and a larger fraction of households without assets relative to those without income. The top 1% of the net worth distribution has 35% of assets, and the top 0.1% holds 13% of total wealth. Earnings are also concentrated: the share of the top 1% earners is 17%, and that of the top 0.1% is 6%.

There is a strong correlation between wealth, earnings and income. This can be seen in Table 2, which shows the wealth shares of different earning and income groups. The top 1% of earners hold about 19% of wealth. Similarly, the households in the highest 1% of incomes hold 27% of wealth in the US. If the correlation were zero, wealth shares would be equal to population shares when ranking groups by income or earnings. This suggests that savings out of earnings and income play a significant role for wealth accumulation.

3.3 The share of income from labor

Figure 1 shows the factor composition of income for top income and wealth groups. The gray bars show the share of wage and salary in total income, as reported by households. The red solid bars show the labor share of total income, including imputed earnings for those

⁵We show in Section 8 that any such bias would have to be much larger than what can be attributed to unrealized capital gains to overturn our results.

Table 2: Shares of Net Worth by Income and Earning Groups

Top percentile of ...	0.1%	0.5%	1%	5%	10%	20%	40%
... income	0.08	0.19	0.27	0.50	0.60	0.70	0.81
... earnings	0.04	0.12	0.19	0.37	0.46	0.57	0.67

Note.— Table shows cumulative shares of net worth held by top income and earning groups. Income includes capital gains. Source: SCF 2001 – 2019.

proprietors who do not report wage income from their businesses. The whiskers on each bar indicate the values when capital gains are included in or excluded from total income. The height of each bar represents the average of the two.

Overall, 74 to 84 percent of net income is attributed to labor, depending on the treatment of capital gains and business income.⁶ Most households rely primarily on wage and salary income. Outside the top 1 percent of the income distribution, labor income makes up at least two-thirds of income. Since business income and capital gains are not an important source of income for these groups, the particular definition of income does not change this.

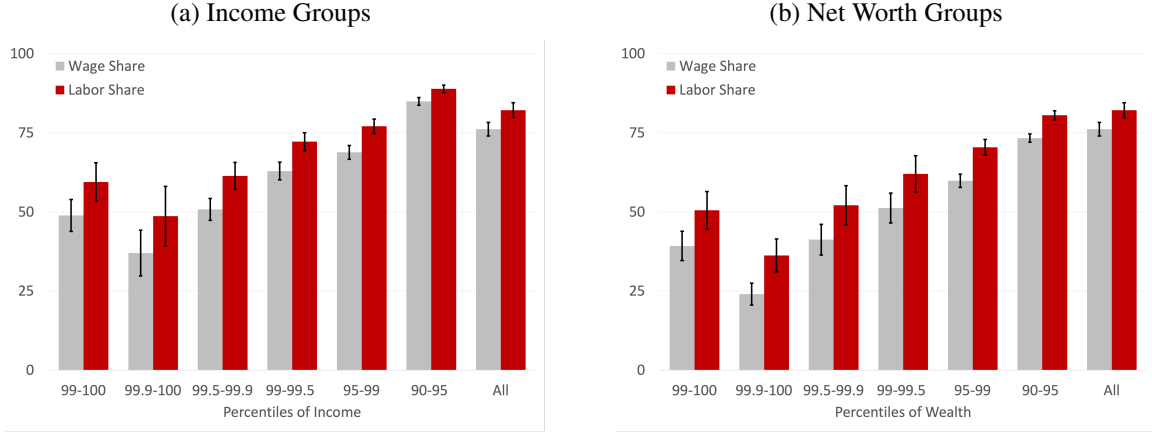
For the top 1% of the income distribution, labor income constitutes 53% of total income when capital gains are included, and 66% when they are excluded. The wage share, which excludes imputed wages for some proprietors, is roughly 10 points lower. Columns 2 to 4 show the percentiles of income within the top 1%. Income from labor is the major source, accounting for at least half of total income, with the exception of the top 0.1%.

A similar pattern is observed among wealth groups in Panel (b). Labor’s share of income for the wealthiest 1% is 45% and 56%, with and without capital gains. Excluding capital gains, income from labor is the main source of income for households outside of the top 0.1% of the net worth distribution. With capital gains, income from capital dominates labor for those in the top 0.5%.

In the Appendix, we document similar patterns in administrative tax data (see Table B.2). Both sets of data agree on the relative shares of sources of income. For most households, earned income from labor is the primary source of income. As we move up the income ladder, the share of labor income declines, and income from capital increases. Nonetheless, even among the top 1% of households (and tax units), at least about half the income can be attributed to labor. The upshot is that labor income remains a non-negligible source of

⁶Since the accounting convention is to report the net income from capital, i.e., excluding depreciation, the share of labor income in net income is higher than its share in gross income typically used to calibrate macro models. We use net capital income in our comparisons of the model predictions below with the data above.

Figure 1: Labor Component of Income by Income and Wealth Groups (%)



Note.— Figure shows wage and labor shares of total income by percentiles of income and net worth. Labor income includes imputed wage income for active business owners who do not draw a salary from their businesses. The whiskers show the shares with and without capital gains in total income. The bar heights show the average of the two values. See Appendix Table B.1 for the data values. Source: SCF 2001 – 2019.

income throughout, and is a primary source of income for most households (or tax units) outside the highest income and net worth groups.

3.4 Implied heterogeneity in the rate of return on assets

Next, we demonstrate how labor's share of income can help identify heterogeneity in the rate of return and discuss the limitations of inference based on cross-sectional data alone.

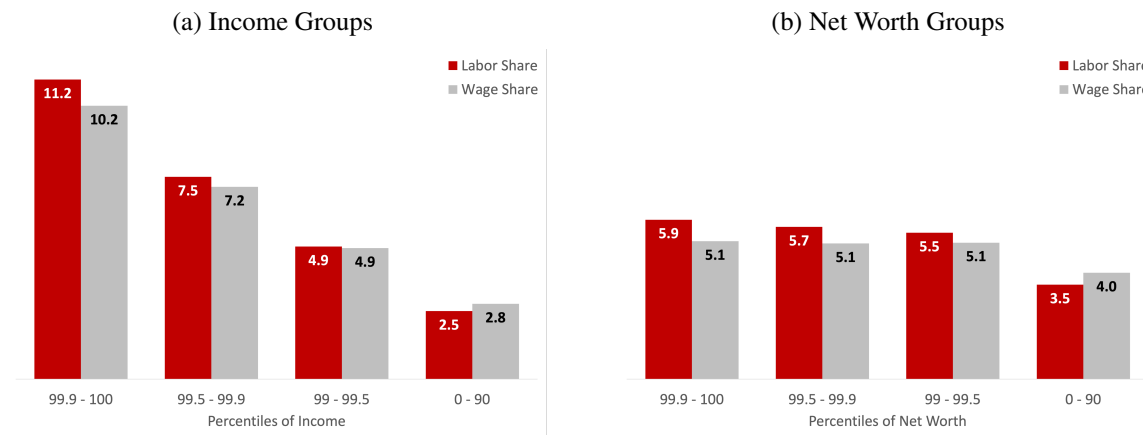
A group's relative rate of return on capital can be inferred from its relative labor share of income. To see this, let $\lambda_i = e_i / (e_i + r_i k_i)$ denote the labor income share of a group of households i , where e_i and k_i are average earnings and assets of a household in the group, and r_i is the group-specific return on assets. Let $i = 0$ represent a base group, which we define below as the bottom 90% of the income or wealth distribution. Denote the earnings ratio of group i relative to the base group by $e_{i/0} = e_i / e_0$, and the asset ratio by $k_{i/0} = k_i / k_0$. Then the labor income share of group i can be expressed as:⁷

$$\lambda_i = \frac{e_i}{e_i + r_i k_i} = \frac{\lambda_0}{\lambda_0 + \frac{k_{i/0} r_i}{e_{i/0} r_0} (1 - \lambda_0)}. \quad (1)$$

Equation (1) relates the labor income share of top income groups to that of the base group.

$${}^7 \lambda_i = \frac{e_{i/0} e_0}{e_{i/0} e_0 + r_i k_{i/0} k_0} = \frac{e_0}{e_0 + \frac{k_{i/0}}{e_{i/0}} r_i k_0} = \frac{e_0}{e_0 + r_0 k_0} \frac{e_0 + r_0 k_0}{e_0 + \frac{k_{i/0}}{e_{i/0}} r_i r_0 k_0} = \frac{\lambda_0}{\lambda_0 + \frac{k_{i/0}}{e_{i/0}} \frac{r_i}{r_0} (1 - \lambda_0)}.$$

Figure 2: Rates of Return Implied by Labor Shares (%)



Note.— Figure shows the synthetic rate of return on assets by household income and net worth implied by the labor share of income, assuming an annual average rate of return of 4.5%. Labor share includes imputed wage income for active business owners who do not draw a salary from their businesses, whereas wage share excludes it (see Figure 1). Authors’ calculations from SCF 2001 – 2019.

Top income groups have lower labor income shares in two situations. First, their relative wealth is higher than their relative earnings, $k_{i/0}/e_{i/0} > 1$, or, equivalently, their wealth-to-earnings ratio is relatively higher. This could arise if, for instance, the saving rate increases with earnings. Second, they have a higher rate of return on their assets: $r_i/r_0 > 1$. To isolate the latter, we solve equation (1) for the relative rates of return, implied by the observed labor income shares for different groups:

$$\frac{r_i}{r_0} = \frac{e_{i/0}}{k_{i/0}} \cdot \frac{1/\lambda_i - 1}{1/\lambda_0 - 1}. \quad (2)$$

Equation (2) allows for an estimate of r_i/r_0 given relative earnings, wealth and labor shares. Figure 2 shows the estimates of r_i across income (Panel a) and wealth groups (Panel b). To translate the relative returns to actual returns, we assume an aggregate return of 4.5% per year, which corresponds to the rate in our quantitative analysis below. Using our preferred labor share measure, the red columns show an annual rate of return of 2.5% for the base income group, with higher rates up along the income ladder. The average return for the top 1% of incomes is 7.9%, and it is 11.2% for the highest income category (top 0.1 percent).

Because the relative rates of return depend on *relative* labor shares, the dispersion is robust to the definition of labor income. The gray bars show the rates implied by excluding imputed wages from labor income (gray bars in Figure 1). The estimated rates of return rise from 2.8% for the base group to 10.2% for the highest income group.

A similar analysis yields smaller differences in rates of return by wealth (Panel b), because top wealth groups have dramatically more assets. This almost suffices to explain their higher share of income from capital, leaving a smaller role for rates of return.

While Figure 2 suggests a modest degree of *cross-sectional* heterogeneity in asset returns, it is not possible to accurately gauge how much this matters for wealth concentration. Since higher rates of return lead to higher income and, ultimately, higher wealth, the positive correlation between rates of return and income (or wealth) may be spurious. Moreover, the dynamic process for the rates of return cannot be estimated from cross-sectional data. But the persistence and predictability of returns are crucial for the savings response to these rates for different income and wealth groups. Below, we combine the cross-sectional information above with a model of household saving to quantify the role of earnings concentration and rate of return heterogeneity in shaping the wealth distribution in the US.

4 A Life-Cycle Model of Wealth Accumulation

For the analysis, we employ an overlapping-generations model of life-cycle wealth accumulation under incomplete markets (Huggett, 1996). We augment the model by incorporating idiosyncratic labor income with extraordinary earnings levels, heterogeneity in the return to capital income, and a non-homothetic bequest motive.

4.1 Environment

Each period, a continuum of new agents enter the economy, with a potential life span of J periods, subject to survival probabilities $s(j)$ for each age j . They work for the first $J_r - 1$ periods and then retire. The total population is normalized to one.

Agents have labor and capital incomes. A worker's labor endowment is $z\varepsilon_j$, where z is stochastic, following a first-order Markov process $F_z(z'|z)$, and ε_j is a deterministic component that captures age-dependent improvements in human capital, e.g., from experience. With this endowment, a worker generates a labor income of $wz\varepsilon_jh$, where w is wage per skill unit and $h \in [0, 1]$ is hours worked. Income from capital is $r\kappa k$, where k denotes assets, and $r\kappa$ is an idiosyncratic rate of return that follows a Markov process defined by $F_\kappa(\kappa'|\kappa, z)$. This process potentially allows for a correlation between labor productivity and capital returns, which could arise in models with entrepreneurs, or in models where some households have restricted access to financial markets.

Once retired, agents collect a pension, $b(z)$, based on the last realization of their labor productivity, z , and continue to earn capital income.⁸ Total income is denoted by y .

In addition to income, agents may stochastically receive a bequest (or an inter-vivos transfer), Φ , according to the state-dependent density F_Φ . As we explain in Section 5.6, the state-dependence allows us to capture age profiles of the incidence and the size of inter-generational transfers, as well as their correlation with parental income and wealth.

All income is subject to taxation, as are large bequests. The tax system, outlined below in detail, distinguishes between different sources of income and features transfers. The disposable income after all taxes and transfers is denoted by y^d . Consumption is subject to sales tax at rate τ_s . The bequest tax function is denoted τ_b . The government uses the tax revenue to finance an exogenously given expenditure level, G , pension payments and other transfers.

Goods are produced by a representative firm using aggregate capital K and labor N with a Cobb-Douglas production function: $Y = \Psi K^\alpha N^{1-\alpha}$. The firm hires capital and labor in a competitive market to maximize its profits.

4.2 The consumption-savings problem

Agents value consumption, leisure, and the assets they leave for their offspring. An agent's problem is to choose labor supply, consumption, savings and bequests to maximize expected lifetime utility. Future utility is discounted by $\beta \in (0, 1)$. At each period j , agents are informed of their labor endowment, $z\varepsilon_j$, and their rate of return, $r\kappa$, prior to taking their decisions. Formally, the Bellman equation for a worker's problem is

$$V(j, k, z, \kappa) = \max_{c, k' \geq 0, h \in [0, 1]} \left\{ \frac{c^{1-\sigma_c}}{1-\sigma_c} - \theta \frac{h^{1+\sigma_l}}{1+\sigma_l} + \beta(1-s(j))\phi(k') \right. \\ \left. + \beta s(j)\mathbb{E}[V(j+1, k' + \Phi', z', \kappa') | j, z, \kappa] \right\}$$

subject to

$$(1 + \tau_s)c + k' = y^d(zw\varepsilon_j h, r\kappa k) + k + Tr,$$

where $\phi(k) = \phi_1 [(k + \phi_2)^{1-\sigma_b} - 1]$ is the utility value of bequeathed assets, and Φ' denotes assets received as a bequest, net of any applicable tax. The expectation is taken over the

⁸The actual US Social Security benefits depend on a worker's average earnings over their career. Following [Kindermann and Krueger \(2022\)](#), we assume that pension benefits depend on the earnings of the last working age period. This allows us to capture the redistributive structure of the US pension system while maintaining computational feasibility.

future values of the labor endowment, z' , the rate of return on assets, κ' , and Φ' , given the processes F_z , F_κ and F_Φ .

Since retirees do not work, the Bellman equation for a retiree's problem is given by

$$V(j, k, z, \kappa) = \max_{c, k' \geq 0} \left\{ \frac{c^{1-\sigma_c}}{1-\sigma_c} + \beta s(j) \mathbb{E}[V(j+1, k' + \Phi', z, \kappa') | j, \kappa, z] + \beta(1-s(j))\phi(k') \right\}$$

subject to

$$(1 + \tau_s)c + k' = y^d(b(z), r\kappa k) + k + Tr.$$

4.3 Stationary equilibrium

Let $s = \{j, k, z, \kappa\} \in S$ be a generic state vector. The stationary equilibrium of the economy is given by a consumption function, $c(s)$, a savings function, $k'(s)$, labor supply, $h(s)$, a value function $V(s)$, a wage rate w , an interest rate r and a distribution of agents over the state space $\Gamma(s)$, such that (i) functions $V(s)$, $c(s)$, $k'(s)$ and $h(s)$ solve the consumers' problems, (ii) firms maximize profits, and (iii) factor markets clear:

$$K = \int k(s) d\Gamma(s) \quad N = \int z\varepsilon_j h(s) d\Gamma_{j < J_r}(s),$$

the government's budget is balanced:

$$\begin{aligned} G + \int b(z) d\Gamma_{j \geq J_r}(s) &= \tau_s \left[\int c(s) d\Gamma(s) \right] + \int [y - y^d(zw\varepsilon_j h, r\kappa k)] d\Gamma_{j < J_r}(s) \\ &\quad + \int [y - y^d(b(z), r\kappa k)] d\Gamma_{j \geq J_r}(s) + \int (1-s(j))\tau_b(k') d\Gamma(s). \end{aligned}$$

and $\Gamma(s)$ is consistent with the policy functions and is stationary.

5 Calibration of the Model

To quantify the model parameters, we first choose a set of parameters based on information that is exogenous to the model. Then, we calibrate the remaining parameters so that the stationary equilibrium of the model economy is consistent with the empirical distributions of earnings, income and wealth, as well as other informative data moments. Below, we describe our calibration strategy and highlight the key assumptions. We report a full list of calibration

results, including target moments and parameter values, in Appendix C.

While our approach is broadly consistent with the standard for quantitative macro models of overlapping generations with idiosyncratic risk, it has some distinctive elements. From a modeling perspective, the main differences are in the earnings process, where we allow some households the possibility of reaching an extraordinarily high labor productivity level, and in the rate of return risk. From an empirical point of view, we differ from earlier studies in our explicit use of the joint distribution of earnings, income and wealth in addition to their marginal distributions to identify these modeling extensions.

5.1 Demographics

The model period is five years. The first period corresponds to ages 20 to 24. Retirement is mandatory at age 65 ($J_r = 10$) and death is certain after $J = 16$ (ages 95-99). Following Halliday et al. (2019), we model survival probability as a logistic function of age: $s(j) = [1 + \exp(\omega_0 + \omega_1 j + \omega_2 j^2)]^{-1}$ and use their recommended parameter values.

5.2 Preferences and production technology

Preferences are described by a discount factor, β , the inverse elasticity of intertemporal substitution, σ_c , the inverse elasticity of labor supply, σ_l , the disutility of work θ and the parameters of utility from bequests: σ_b , ϕ_1 and ϕ_2 . We discuss the last three separately below. We set $\sigma_l = 1.22$, which implies a Frisch elasticity of 0.82, the average of 0.68 for males and 0.96 for females reported by Blundell et al. (2016). We choose θ so that an average household allocates 35% of their time to work in equilibrium. We set $\sigma_c = 1.5$, in the middle of the range typically used in the literature. The discount factor, β , is chosen so that the ratio of capital to (annual) income is 3 given an annual depreciation rate of 4.5%. This results in a value of $\beta = 0.88$ (0.974 per annum). The implied (value-weighted) interest rate that clears the asset market is 4.5%. We normalize the equilibrium wage rate, $w = 1$, which requires an aggregate TFP of $\Psi = 1.55$. To set capital's share in output, we target the net labor income share observed in the SCF.

5.3 Labor productivity process

The stochastic component of labor productivity takes eight values. Six of these are ordinary states, and the other two are extraordinary states that generate exceptionally high earnings

levels. The ordinary levels z_1 to z_6 consist of combinations of two components: a permanent component, $f \in \{f_H, f_L\}$, that is fixed over a household's career, and a transitory component, $a \in \{a_L, a_M, a_H\}$. Individuals randomly draw their value of f in the first period of their lives. Idiosyncratic fluctuations in labor income are captured by a 3-by-3 matrix $A = [A_{ij}]$ with $i, j \in \{L, M, H\}$ and $\sum_j A_{ij} = 1 - \lambda_{in}$, as well as by λ_{in} , which represents the probability of entering an extraordinary state of productivity. The stochastic labor productivity process is summarized by the matrix in Table 3. The following additional assumptions are explicit in the formulation of the matrix. The probability of reaching an extraordinary status, λ_{in} , is independent of one's current productivity state and age. Likewise, if a household loses its extraordinary status, then it is equally likely to transition to any one of the ordinary states.

Table 3: Transition Matrix for the Labor Productivity Process

	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8
	$f_L + a_L$	$f_L + a_M$	$f_L + a_H$	$f_H + a_L$	$f_H + a_M$	$f_H + a_H$		
$f_L + a_L$	A_{11}	A_{12}	A_{13}	0	0	0	λ_{in}	0
$f_L + a_M$	A_{21}	A_{22}	A_{23}	0	0	0	λ_{in}	0
$f_L + a_H$	A_{31}	A_{32}	A_{33}	0	0	0	λ_{in}	0
$f_H + a_L$	0	0	0	A_{11}	A_{12}	A_{13}	λ_{in}	0
$f_H + a_M$	0	0	0	A_{21}	A_{22}	A_{23}	λ_{in}	0
$f_H + a_H$	0	0	0	A_{31}	A_{32}	A_{33}	λ_{in}	0
z_7	λ_{out}	λ_{out}	λ_{out}	λ_{out}	λ_{out}	λ_{out}	λ_{ll}	λ_{lh}
z_8	0	0	0	0	0	0	λ_{hl}	λ_{hh}
initial dist.	$\zeta/4$	$(1 - \zeta)/2$	$\zeta/4$	$\zeta/4$	$(1 - \zeta)/2$	$\zeta/4$	0	0

Note.— The transition probabilities from the state in Column 1 to the states in Columns 2 to 9. The last row shows the initial distribution of young workers across the productivity states at the time of labor market entry.

Our working assumption is that the values for the ordinary states and the transitions among them can be inferred from survey data, unlike the transitions to, from and among extraordinary states. To calibrate values and transitions of ordinary states, we assume that the transitory component, a , follows an AR(1) process, with an annual persistence of 0.97, as estimated by Heathcote et al. (2010), and variance σ_a . Wage regressions in the PSID with fixed worker effects indicate that 60% of the total variance of wages reflects differences in the permanent component, and the remaining 40% reflects transitory shocks. Accordingly, we set $\sigma_a^2 = 0.4\sigma^2$, where σ^2 is the total variance. Normalizing $a_M = 0$ and setting $a_L = -a_H < 0$ then allows us to determine a_L and the elements of A in terms of σ using the Rouwenhorst approximation. To determine the levels of the fixed components, we set $f_L =$

$-f_H$. Assuming an equal division of households between the two permanent states, we then express f_H in terms of σ such that the implied variance is $0.6\sigma^2$.

At this point, all ordinary productivity levels are expressed relative to σ . Note that σ^2 is the variance corresponding to the long-run stationary state associated with the transition matrix. Since the wage distribution is not stationary over the life cycle, this object is not directly observed in the data. To determine σ , we parameterize the initial distribution of households over the ordinary productivity states at the beginning of their careers as in the last row of Table 3. By assumption, households are not born to extraordinary productivity. Then, given the age distribution implied by the survival function described in Section 5.1, we jointly calibrate the parameters ζ and σ such that the overall cross-sectional variance of wages equals 0.58 and the standard deviation of wages grows by 47 percent between the ages of 22 and 57, as in the PSID. This requires that $\sigma^2 = 0.81$ and $\zeta = 0.18$.

This leaves the extraordinary productivity levels z_7 and z_8 , and the transition probabilities $(\lambda_{in}, \lambda_{out}, \lambda_{ll}, \lambda_{lh}, \lambda_{hl}, \lambda_{hh})$. Two of these are pinned down by adding-up constraints for probabilities. To identify the remaining parameters, we target the marginal distribution of earnings, specifically, the top 0.1 and 1 percent shares, the labor income shares of the top 0.1, 1 and 10 percent of the income distribution, as well as the probability of remaining a top 1% earner as reported by [Kopczuk et al. \(2010\)](#) from administrative data.

The stochastic process for labor productivity is combined with a deterministic age profile of wages common to all workers (ϵ_j) . We calibrate this profile to that from the PSID.

5.4 Rate of return process

The rate of return on capital is stochastic and takes three values, $\{r\kappa_L, r\kappa_H, r\kappa_{top}\}$, where r is the (common) equilibrium rate of return, and the κ_i are the relative idiosyncratic returns. The transitions between these states are governed by the following transition matrix, which might depend on labor productivity z :

$$\Pi_{\kappa}(z) = \begin{pmatrix} & \kappa_L & \kappa_H & \kappa_{top} \\ \kappa_L & \pi_{ll} & 1 - \pi_{ll} - \pi_{in}(z) & \pi_{in}(z) \\ \kappa_H & 1 - \pi_{hh} - \pi_{in}(z) & \pi_{hh} & \pi_{in}(z) \\ \kappa_{top} & 0 & 1 - \pi_{top,top} & \pi_{top,top} \end{pmatrix}$$

We assume that $\pi_{in}(z)$ is identical for ordinary productivity levels (z_1, \dots, z_6) but may take on different values for extraordinary states (z_7, z_8) . If π_{in} is larger for the latter, our calibration

admits a positive correlation between productivity and rates of return.

Since asset returns are not directly observed in the data, we target moments on wealth concentration, intergenerational wealth mobility and relative returns of different income and wealth groups to identify the elements of $\Pi_{\kappa}(z)$. The targets are the top 0.1%, 1%, 5% and 10% wealth shares, returns of the top 0.1 and 1 percent income and wealth earners relative to the aggregate return, as well as the intergenerational probabilities of staying in the fourth and fifth quintiles of the age-adjusted wealth distribution. Values for the relative return targets are computed in our analysis of returns in Section 3 above. Using data from the PSID for the period from 1984 to 1999, [Charles and Hurst \(2003\)](#) report the latter two moments to be 0.26 and 0.36, indicating substantial persistence of wealth across generations. We replicate their estimation method in our model to compute the corresponding model moments.

5.5 Tax and transfer system

Taxes are levied on personal income, corporate income, sales and estates to support exogenous government expenditures, transfers to households, and pensions.

Corporate taxes are modeled as a flat rate, τ_c , levied on a portion of capital earnings before households receive their income. We set $\tau_c = 23.6\%$, which is the average effective marginal tax rate on corporate profits in 2010 as estimated by [Gravelle \(2014\)](#). Since most capital income is not subject to corporate income tax, we levy τ_c on capital income above a threshold d_c , and set d_c such that the corporate tax revenue is 2.5% of GDP. We set the sales tax rate to 5% following [Kindermann and Krueger \(2022\)](#).

Personal income taxes are applied to earnings, non-corporate capital income and pension income. Following [Kaymak and Poschke \(2016\)](#), we model disposable income to be log-linear in taxable income, augmented to cap the marginal tax rate at 39.6%.⁹ We calibrate the progressivity of the income tax system to the difference between the average income tax rate paid by the top 1% and the bottom 99% of the income distribution. [Piketty and Saez \(2007\)](#) report this value to be 12.4%. We choose the average tax rate to balance the government's budget.

Finally, there is a progressive estate tax system τ_b . Following [De Nardi and Yang \(2016\)](#), we model it as a flat 20% tax on the largest 2% of estates. This mimics the US data, where only 2% of estates incur estate taxes.

⁹This formulation of the income tax system captures net transfers that are non-monotone in income, such as the earned income tax credit and welfare-to-work programs. See Appendix C for the formal representation and [Guner et al. \(2014\)](#), [Heathcote et al. \(2017\)](#) and [Bakiş et al. \(2015\)](#) for evidence on the fit of this function.

Tax revenue finances exogenous expenditures, pension payments and transfers. The expenditures are set at 11.6% of GDP, which brings the sum of expenditure and transfers to 22.2% of GDP. This number corresponds to revenue from Social Security contributions and taxes present in the model, as reported in NIPA Tables 3.1 through 3.3. In addition, the government makes transfers in the form of disability benefits, veterans benefits, etc. In the data, these transfers represent 2.7% of GDP. We set Tr accordingly.

Pension benefits are modeled after the US Social Security system as described in the US Social Security Bulletin ([Social Security Administration, 2013](#)) (see Appendix C).

5.6 Bequests

The utility value of leaving a bequest is $\phi(k) = \phi_1[(k + \phi_2)^{1-\sigma_b} - 1]$, where ϕ_2 captures the degree of non-homotheticity and ϕ_1 represents overall altruism. We calibrate ϕ_1 and ϕ_2 to match the bequest-to-wealth ratio reported by [Guvenen et al. \(2023\)](#) and the share of the largest 2% of bequests in total bequests, which is 40% ([Feiveson and Sabelhaus, 2018](#)). We calibrate the curvature of the bequest function, σ_b , to match the age-wealth profile in the SCF.

Bequest receipt in the model can occur at any age between 25 and 85. At each age, agents receive a transfer with probability, p_Φ^j . The size of the bequest is randomly determined depending on the agent's age, j , labor productivity, z , and asset return, κ . In our model, the total size of the estates in the economy comprise of savings of the deceased: $E = \int (1 - s(j))k'(j, k, z, \kappa)d\Gamma$. We allocate a fraction, γ_j , of this total to surviving agents of age j . We then allocate $\gamma_j E$ between these agents based on their labor productivity, z , and their asset return, κ . Specifically, we divide z and κ states into two groups each, low versus high, and let agents draw from among the estates of the deceased who have the same labor productivity as theirs with probability $\bar{\gamma}_z$ and the same asset return as theirs with probability $\bar{\gamma}_\kappa$.¹⁰ This allows for intergenerational correlations in wealth by ensuring that the bequests are more likely to come from a parent with similar characteristics. Concretely, if $\bar{\gamma}_z (\bar{\gamma}_\kappa) > 1/2$, high-productivity (high-return) children are more likely to receive a bequest from a high-productivity (high-return) parent.

For the quantitative analysis, we set the age-specific transfer receipt probability, p_Φ^j , to the fraction of households who receive a bequest or an inter-vivos transfer at each age in the data, as reported in [Feiveson and Sabelhaus \(2018\)](#). Similarly, we set γ_j to match the size distribution of total bequests by age group, also reported in [Feiveson and Sabelhaus \(2018\)](#).

¹⁰Low productivity states comprise of z_1 to z_3 , and the low return state is κ_L .

Figure 3: Distribution of Wealth, Income and Earnings



Note.— Panel (a) shows the cumulative shares for the top percentile groups. Panel (b) shows the share of net worth held by top income and earning groups. Data values come from SCF 2001 - 2019. Income includes capital gains.

We then calibrate $\bar{\gamma}_z$ and $\bar{\gamma}_\kappa$ internally to match the inter-generational correlation of 0.3 in wages (Solon, 1992) and of 0.37 in wealth (Charles and Hurst, 2003).

6 The Benchmark US Economy

In this section we discuss the fit of the model to the distributions of earnings, income and wealth, followed by a discussion of the earnings and rate of return processes implied by the calibration. We also compare the model's implications for the evolution of earnings, income and net worth over the life cycle to the data.

6.1 Distributions of earnings, income and net worth

Figure 3 depicts the distributions of earnings, income and net worth in the model (markers) and in the data (lines). Panel (a) shows the marginal distributions for top percentiles of each variable. The model captures the high concentration of net worth among top fractiles. This implies that the model replicates the Pareto tail of the empirical distribution of net worth.¹¹

¹¹The wealth shares of the wealthiest 0.01 and 0.001 percent in the model are consistent with a Pareto tail index of 1.42. The corresponding empirical estimates are 1.52 based on the Forbes list (Vermeulen, 2018) and 1.37 based on capitalization based estimates of the top 0.01% wealth share (Piketty et al., 2018).

Table 4: Share of Income from Labor by Income Groups

	All	Top Percentiles			Quintiles				
	0-100	Top 0.1%	Top 1%	Top 10%	5th	4th	3rd	2nd	1st
Data	0.82	0.49	0.59	0.72	0.77	0.93	0.92	0.84	4.98
Model	0.79	0.49	0.59	0.71	0.76	0.86	0.84	0.80	0.18

Note.— Data values come from the SCF (2001 - 2019).

The overall Gini coefficient for net worth, which is not a calibration target, is 0.804 in the model – slightly below the data value of 0.84. This discrepancy is driven by a small number of households with negative net worth in the data, which are absent in the model. The SCF Gini coefficient excluding these households is 0.807. The concentration of income and earnings among top groups is otherwise in line with the data.

Panel (b) shows the shares of net worth held by different income and earnings groups, which is not directly targeted in the calibration. The model closely matches their joint distribution with the exception of wealth shares of incomes between the 95th and the 99th percentiles.

Next, we compare the factor composition of income for different income groups in Table 4. Labor’s share of income is 49% (59%) in the model for the top 0.1% (1%) of incomes, exactly as in the SCF data. Labor’s share for the wealthiest 1%, which is not targeted in the calibration, is 42%, somewhat below the data value of 50%.

Overall, the model features a highly skewed wealth distribution with a realistic correlation between earnings and wealth and a realistic role for labor among top income and wealth groups. Next, we discuss the underlying processes for labor productivity and capital returns.

6.2 Labor productivity process

The model replicates the empirical concentration of earnings in the cross-section. The extraordinary productivity states are critical for this. Workers in these states (z_7 and z_8) are 19 and 160 times as productive as the average worker, and they represent 0.76% and 0.03% of the population in equilibrium.¹² But earnings are a combination of productivity and hours worked. The earnings of the top 0.1 and 1 percent of earners are 50 and 16 times the average

¹²The transition matrix for the calibrated productivity process and the corresponding levels are shown in Appendix Table C.1.

in the model, close to their empirical values of 60 and 17.

The distribution of earnings growth, which determines the earnings risk faced by top earners, is also reasonable. [Guvenen et al. \(2021\)](#) characterize the earnings growth of the top 1% by a large standard deviation (1.1), a high degree of kurtosis (10), and negative skewness (-1.5). The model economy features a standard deviation of 1.6, a kurtosis of 11, and a skewness of -2.9, which are comparable to the data, even though they aren't explicitly targeted.¹³ The highest earning levels are slightly less persistent than ordinary levels: the probability of remaining among the top 1% of earners after 5 years is 64% in the model, almost identical to the estimate of 62% by [Kopczuk et al. \(2010\)](#).¹⁴

Overall, the estimated earnings process captures fundamental properties of the earnings distribution well. It closely matches the cross-sectional distribution of earnings while also capturing the dynamic aspects of earnings growth.

6.3 Rate of return heterogeneity

Differences in returns on wealth are substantial (see Appendix Table C.2). The calibrated annual rates are 0, 6.7% and 22.7%. But only around 0.1% of households enjoy the top rate, and about 40% of them have the medium rate. All rates are fairly persistent with retention probabilities between 0.90 and 0.96 over 5 years, but because they are not permanent, the dispersion in average lifetime rates of return across households is much smaller than in the cross-section: the average (unweighted) return is 2.7%, with a standard deviation of 3.34%.¹⁵

The calibration implies a positive correlation between the top earner status and the top investor status. Households with the highest labor productivity are 15 times more likely to enter the top return state than an ordinary household (Panel b of Table C.2). As a result, 1% of households in the top productivity state are also in the top return state, compared to just 0.1% for the population overall.

Figure 4 compares the average rates of return by income and wealth in the model (gray) with the data (red). Since we explicitly target the rates of return for the top 0.1 and 1% income and wealth groups relative to the mean return, the model fits the data values closely: top income and wealth groups have significantly higher returns.¹⁶ This reflects both the higher

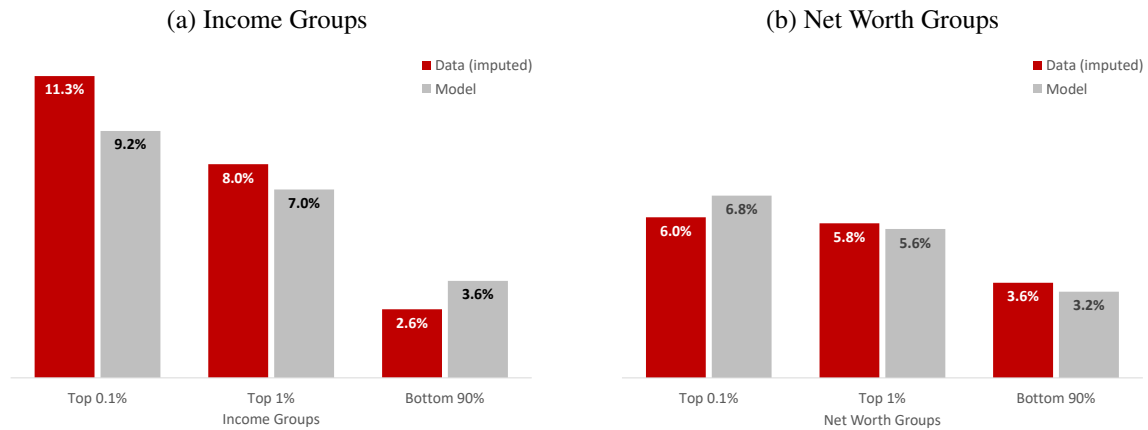
¹³The excess skewness is partly due to our assumptions on λ_{out} . It is significantly less pronounced when all those leaving z_7 downward enter z_6 . Yet, this change hardly affects our quantitative findings below.

¹⁴These studies are based on individual earning records from the Social Security Administration. [Auten et al. \(2013\)](#) find a comparable level of persistence for income among tax units.

¹⁵This compares to a standard deviation of fixed effects of asset returns of 2.8% measured by [Fagereng et al. \(2020\)](#) in longitudinal Norwegian data.

¹⁶Because the rates of return vary more with income than with wealth in the data (Figure 2), the model

Figure 4: Rates of Return by Wealth and Income: Model vs. Data



Note.— Figure shows the rates of return on assets by household income and net worth implied in the model. Data values are authors’ calculations from the 2001 to 2019 waves of the SCF. See Figure 2 for explanations.

propensity of the most productive households to enter the top return state and the eventual feedback effect from those high returns to capital income. Note that the scale dependence between wealth and rates of returns is not hardwired in the model—it emerges endogenously, since households with higher returns are more likely to be wealthy.

6.4 Implications for life-cycle dynamics

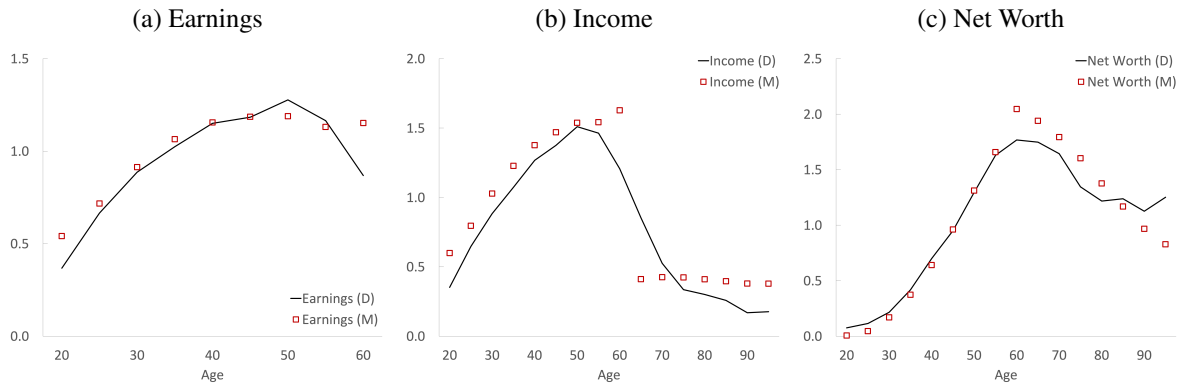
Next, we compare the model’s implications for the evolution of income, earnings and wealth over the life cycle with the data. Figure 5 shows average earnings, income and wealth by age. As in the data, young households start with near-zero wealth, accumulate assets with savings out of income until retirement, and dissave thereafter. The model mimics this accumulation phase very closely and only slightly overshoots around the retirement age, which is common to all agents in the model, but likely varies by a few years in the data. After that, the model matches the pace of asset decumulation closely until the age of 85.¹⁷

Earnings generally increase with age in a concave fashion and decrease slightly near retirement. Note that earnings reflect households’ labor supply decisions given the age pro-

slightly undershoots average returns of top income groups, and slightly overshoots that of top wealth groups.

¹⁷The two remaining age groups, who account for about 1% of the population in the SCF, do not decumulate wealth in the data. An increase in wealth at the end of life is incompatible with standard life cycle models. It may reflect wealth-dependent survival rates in the data, which are absent in the model. We do not expect this discrepancy to affect our results, as the total gap between between the model and data wealth holdings of these groups corresponds to only 0.17% of total wealth.

Figure 5: Earnings, Income and Wealth over the Life Cycle



Note.— Solid lines depict the life-cycle profiles of average earnings, income and net worth implied by the benchmark calibration. Dashed lines show the data values from the SCF.

files of wages, which we target, and wealth, which we do not. Similarly, income rises until retirement, and is flat after retirement.¹⁸

Figure 6 compares the evolution of earnings and wealth dispersion with the data. The rise in earnings dispersion is governed by the productivity process described in Table C.1. Earnings inequality grows mainly because the wages of young households are similar to each other. With age, some households move to higher earning states and some to top earning states.

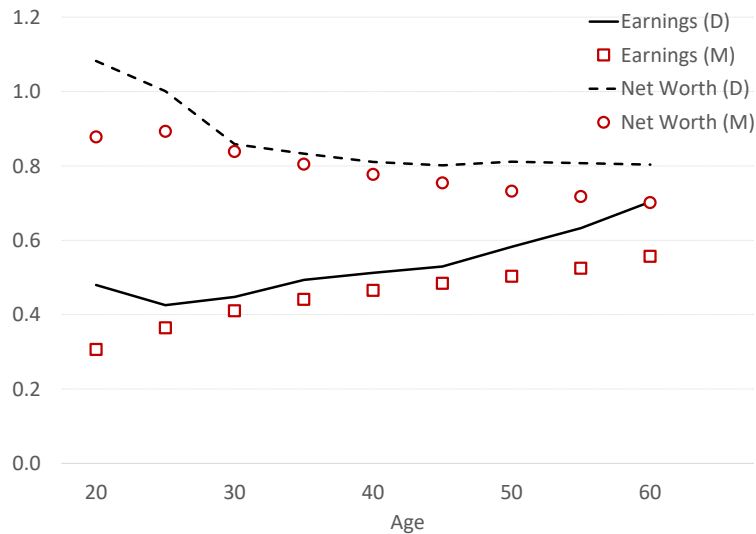
The Gini coefficient for wealth is initially high, because most young households have few assets and weak saving motives in anticipation of earnings growth.¹⁹ With age, asset accumulation becomes more prevalent as earnings grow and retirement approaches. This reduces the Gini coefficient early on in the life cycle. In later stages of the life cycle, the reduction in the wealth Gini is offset by the increasing dispersion in earnings and income, which tends to raise wealth dispersion, resulting in a stable dispersion of wealth for middle-aged groups and older, as in the data.

Overall, the model provides an accurate description of the distributions of earnings, income and wealth. The productivity process captures the salient features of earnings growth both in the short run and over the life cycle. The factor composition of income is realistic,

¹⁸The model also generates plausible age profiles across the distributions. For instance, the average age in the top 1% of wealth (income) is 64 (58) years in the model, compared to 60 (55) in the data.

¹⁹In the data, the Gini coefficient for the youngest group is above 1 because of a few households with negative net worth. Excluding those from the sample lowers the Gini coefficient to 0.86.

Figure 6: Earnings and Wealth Inequality over the Life Cycle



including at the top of the distribution, and the implied rates of return by income and wealth are broadly in line with the data. The wealth distribution is highly concentrated at the top and correlated with earnings and income, as in the data. Next, we assess the quantitative significance of different modeling elements for wealth concentration.

7 Determinants of Wealth Concentration

In this section, we quantify the relative roles of earnings concentration, rate of return differences and bequests in shaping wealth concentration. To do so, we shut down different model components and compare the implied wealth concentration with the benchmark economy. Table 5 shows the decomposition results. The first row reports the benchmark measures of earnings and wealth concentration. The next three rows show the effect of taking away a critical model component individually and report the counterfactual moments. The remaining rows remove combinations of components.

First, we consider the effects of bequest inequality by simulating an economy where bequests are distributed equally (counterfactual 1). In this scenario, the Gini coefficient for wealth drops substantially, from 0.80 to 0.73, roughly the difference between Canada and the US. Top 1% and 0.1% wealth shares fall by 30% and 40%. Overall, bequest inequality has a significant impact on the wealth distribution, as it perpetuates wealth concentration across

Table 5: Determinants of Wealth Concentration: A Decomposition Analysis

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
(0) benchmark	0.80	0.15	0.35	0.05	0.16
<i>counterfactual economies without ...</i>					
<i>(a) individual channels</i>					
... (1) equal bequests	0.73	0.09	0.24	0.05	0.16
... (2) no top earners	0.74	0.08	0.20	0.004	0.04
... (3) common returns	0.74	0.08	0.26	0.05	0.16
<i>(b) combinations of channels</i>					
... (4) equal bequests & no top earners	0.67	0.03	0.10	0.004	0.04
... (5) equal bequests & common returns	0.70	0.07	0.23	0.05	0.16
... (6) no top earners & common returns	0.65	0.01	0.09	0.005	0.04
... (7) all three channels removed	0.62	0.01	0.07	0.005	0.04

Note.— Results from model simulations. Counterfactual economy (1) fully redistributes all bequests among recipients. Economy (2) sets productivity in the top productivity states z_7 and z_8 equal to the highest ordinary state, z_6 . Economy (3) sets κ to its value-weighted average in the benchmark economy. The remaining counterfactual economies represent different combinations of these scenarios.

generations.²⁰

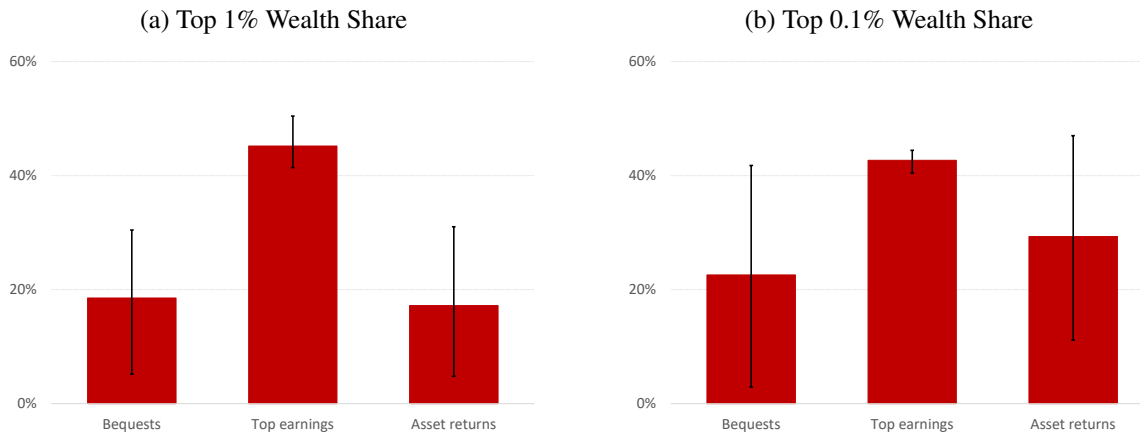
Next, we remove superearners from the benchmark economy by equating the productivity at the two extraordinary states to the highest “ordinary” level: $z_8 = z_7 = z_6$ (counterfactual 2). This preserves the wage distribution among the remaining states.²¹ Earnings concentration drops far below the data in this scenario, with a top 1% earnings share of only 4% versus 17% in the data, and 0.4% for the top 0.1% earners, compared to 6% in the data. This immensely reduces wealth concentration. The wealth share of the wealthiest 1% drops from 35% to 20%, and that of the wealthiest 0.1% from 15% to 8%.²² Because there still is substantial earnings dispersion outside of the top groups, the overall drop in wealth dis-

²⁰In the Appendix, we investigate the role of non-homotheticity, intergenerational links and σ_b . In all three cases, the effects are qualitatively similar to equal distribution of bequests, but quantitatively smaller (Table D.1).

²¹We do not change $\pi_{in}(z)$. Additionally setting $\pi_{in}(z_7) = \pi_{in}(z_8) = \pi_{in}(z_6)$ hardly changes the results.

²²Most of the decline in the top 1% wealth share is due to the change in z_7 , whereas z_7 and z_8 affect the top 0.1% wealth share to a similar extent. (See Appendix Table D.1.)

Figure 7: Factors of Wealth Concentration



Note.— Figure shows the marginal effect of each factor on benchmark wealth concentration. The whiskers show the range of effects obtained by permuting the order in which factors are eliminated from the benchmark economy. The column height represents the average across permutations.

person, while sizable, is less extreme—the Gini coefficient drops from 0.80 to 0.74. An additional reduction in earnings inequality below the top of the earnings distribution would further reduce the Gini coefficient.

Finally, we equalize rates of return by setting κ_i to its value-weighted average in the benchmark economy for all households (counterfactual 3). Doing so reduces the Gini coefficient for wealth from 0.80 to 0.74 and the top 1% wealth share from 35% to 26%. The top 0.1% share falls strongly, from 15% to 8%. These are significant reductions in top wealth shares.²³

Overall, removing each component individually reveals comparable drops in the Gini coefficient and in the top 0.1% wealth share, while eliminating superarners triggers the largest drop in the top 1% wealth share. But, eliminating the different components individually may mask potential interactions between them. With such interactions, individual elimination of components would yield an incomplete assessment. To measure these interactions, we remove multiple model components at once, permuting the order in which they are removed. We then compute four distinct marginal effects for each component across permutations. For example, top earners can be removed starting in a situation where all channels are active, where only one other channel is active (two permutations), or where only the top earner channel is active. Figure 7 summarizes the range of marginal effects of each component on wealth concentration, showing the reduction in wealth concentration relative to the bench-

²³Most of the reduction in top wealth shares stems from eliminating the top return, as setting $\kappa_{\text{top}} = \kappa_H$ produces a smaller change in the Gini but similar changes in top shares. (See Appendix Table D.1.)

mark economy. The bars represent the average of the four marginal effects. Whiskers show the smallest and the largest marginal effects.

The contribution of top earners to wealth concentration is large in all permutations. On average, removing top earners reduces the top 1% wealth share by 16 percentage points and the top 0.1% share by 6 percentage points (pp). These correspond to 45 and 43 percent of the benchmark values. This effect is stable across permutations, with a maximum reduction in the top 1% (0.1%) wealth share of 50% (44%) percent, and a minimum of 41% (40%).

The mean contribution of bequests and asset returns to top wealth shares is significantly smaller. On average, equalizing bequests reduces top wealth shares by around 20% of the benchmark value. The average effect of return heterogeneity on the top 1% wealth share is similar, whereas the average effect on the top 0.1% is larger, at 29% of the benchmark value.

These results reveal a complementarity between return heterogeneity and bequest inequality in generating wealth concentration. In fact, the effect of removing them jointly (counterfactual 5) barely exceeds that of removing each individually (counterfactual 1 or 3). This implies that the marginal effect of one is much smaller when the other is absent from the economy. (The wide range of marginal effects across permutations is indicated by the whiskers in Figure 7.) Therefore, removing one channel is similar to removing both. Their *joint* effect is comparable to the effect of removing top earners *alone*, as the wealth shares of the top 0.1% and 1% drop to 8 and 20 percent without top earners, and to 7 and 23 percent without the two capital-based components.

This complementarity is also present in terms of wealth inequality outside the top of the distribution, as captured by the Gini coefficient. Again, there is little variation across counterfactuals in the effect of top earners on the Gini: Removing them reduces the Gini by 0.06 to 0.09. Removing bequests *or* heterogeneous returns reduces the Gini by 0.03 to 0.07 and 0.03 to 0.09, respectively. Removing both reduces it by slightly more. The larger combined effect on the Gini relative to top wealth shares is attributable to equalization of bequests, because adding a small amount of wealth to a large group of households considerably lowers the Gini coefficient, without necessarily lowering wealth concentration.

Overall, top earners clearly are the single most important channel for top wealth concentration, about as important as bequest inequality and return heterogeneity combined. The role of return heterogeneity grows as one moves further up the tail of the wealth distribution, and bequests amplify that role by perpetuating wealth inequality across generations.

8 Identification and Robustness

In this section, we conduct a series of alternative calibrations to emphasize the relevance of factor composition of income for our findings above and examine their sensitivity to measurement and model specification.

8.1 Alternative calibrations and the labor share of income

We begin by calibrating two alternative models of wealth concentration, ignoring either return heterogeneity or top earners. We then compare the implied distributions of income, earnings and wealth to the data to underline the sources of identification in our benchmark calibration and highlight the pitfalls from ignoring either channel.

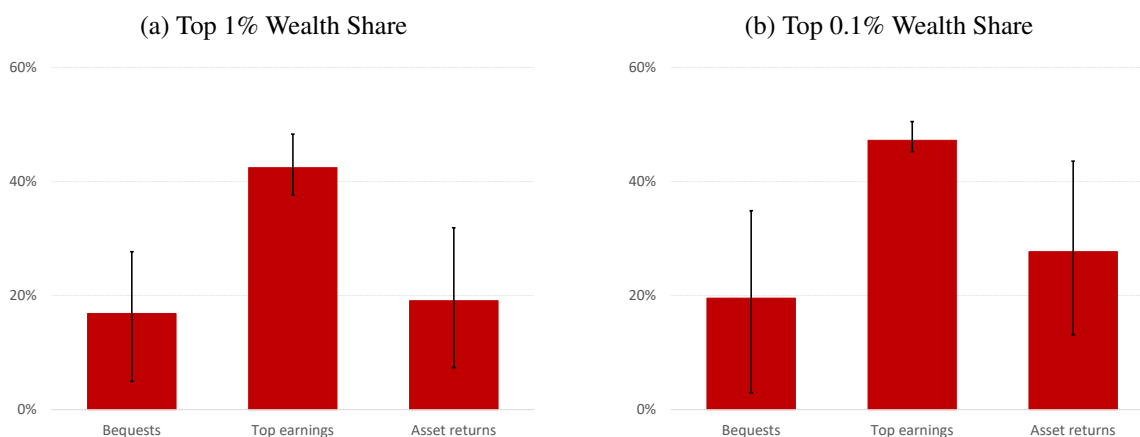
First, we eliminate superearners by setting $z_8 = z_7 = z_6$, and raise the top return to κ_{top} to match the value for the top 0.1% wealth share in the benchmark economy. Second, we set all κ to its asset-weighted mean in the benchmark and raise the highest productivity level (z_8) to match the benchmark top 0.1% wealth share. By construction, both models match the top 0.1% wealth concentration. But they deviate from the data in other dimensions.

The economy without superearners features too low an earnings concentration and an unrealistically low share of labor income for top income and wealth groups. Earning shares of the top 1% and 0.1% plummet to 4% and 0.4%, respectively, much below their empirical counterparts of 17% and 6%. Among top income groups, the implied labor share of income is 30%, half the 59% in the data. Top wealth groups rely almost exclusively on capital income, with a labor share of income of 3%, much below the 50% in the data. This world is reminiscent of [Benhabib et al. \(2019\)](#), whose model, according to our calculations, features a labor share of income among the wealthiest 1% of households between 8% and 21%, depending on the correlation between earnings and wealth in their simulations.²⁴

In contrast, an economy with homogeneous returns features an excessively high labor income share among high income earners, at 75% (78%) for the top 1 (0.1) % of incomes. The top productivity state needs to be more than twice as high, resulting in a counterfactually high earnings concentration with a top 0.1% earnings share of 8% versus 6% in the data. This world is reminiscent of the economy in [Castañeda et al. \(2003\)](#).

²⁴Equation (1) gives the labor share of the wealthiest 1% as a function of their relative assets, $k_{1pct/0} = 33.6$ (from Table 10 in [Benhabib et al. \(2019\)](#)), relative rates of return $r_{1pct/0} = 6.01\%/3.94\%$ (pg. 1638), aggregate labor share, $\lambda_0 = 0.82$ from the SCF, and relative earnings of the wealthiest 1%, $e_{1pct/0}$. The latter figure is not reported. It is bounded from above by the relative earnings of the top 1% *earners* (calculated as 3 from Table 1) – corresponding to perfect correlation of earnings and wealth – and from below by 1, which corresponds to zero correlation.

Figure 8: Factors of Wealth Concentration with Lower Top Labor Income Shares



Note.— Figure shows the marginal effect of each factor on benchmark wealth concentration. The whiskers show the range of effects obtained by permuting the order in which factors are eliminated from the benchmark economy. The column height represents the average across permutations.

Taken together, these exercises illustrate how the labor share of top income groups along with the empirical earnings concentration is crucial to identifying the quantitative drivers of wealth concentration.

8.2 Sensitivity to labor share estimates

Given the importance of the labor share of income in differentiating between modeling approaches to wealth distribution, we next check the sensitivity of the results to some of the assumptions used to compute the factor composition of income. While there are reasons to suspect biases in either direction, we focus on those on the upside in order to bound the significance of earnings heterogeneity from below.

The two issues discussed in Section 3, in particular, relate to the factor composition of business income and to accrued capital gains. Ascertaining the labor share of income among entrepreneurs is inherently difficult. Here, we consider the extreme alternative of allocating all business income to capital. We view this as a conservative case for all other concerns, such as unmeasured capital income, and interpret the results as a lower bound for the relevance of labor income for wealth concentration and an upper bound on the relevance of capital income.²⁵

²⁵Larrimore et al. (2021) report unrealized capital gains to be about 3.3% of income ex capital gains (Table 3, 2000 - 2016 average). For the top 1% of incomes, this suggests a labor share of 0.57, significantly above the 0.49 we consider below.

In what follows, we compute all relevant data moments under this assumption and re-calibrate our model accordingly. When entrepreneurial income is allocated entirely to capital (for those who do not explicitly report salary), labor’s income share among the highest 1% of incomes is 49%, lower than our preferred measure of 59%, but much higher than what is suggested by counterfactual models without top earners. Earnings concentration is slightly lower, with the top 1% claiming 16% of earnings, compared to 17% in the benchmark. The implied relative rates of return also change, from 2.5 and 1.8 times the mean return for the top 0.1% and 1% of the income distribution to 2.3 and 1.7.

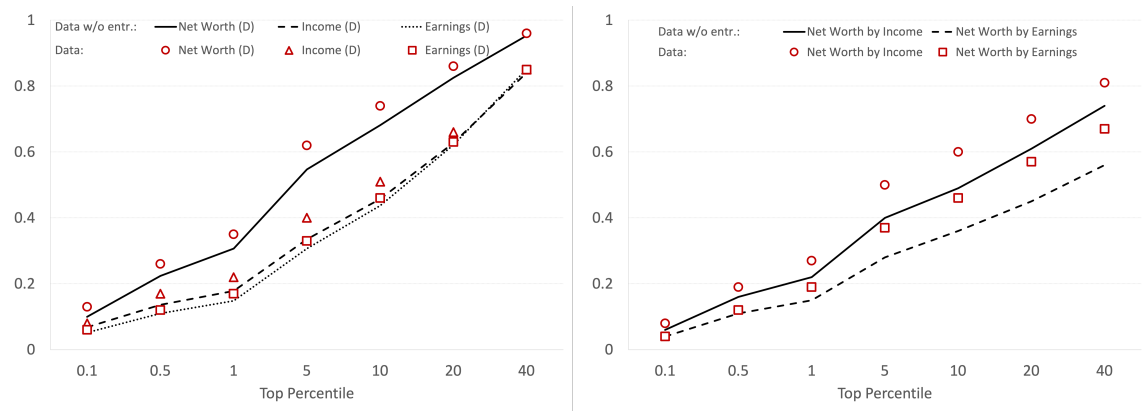
Repeating the decomposition analysis above yields a slightly lower contribution of earnings heterogeneity to wealth concentration, and a slightly higher contribution of return heterogeneity (Figure 8). On average, eliminating top earners now reduces the top 1% wealth share by 14pp instead of 16pp, or 42% instead of 45%. It reduces the top 0.1% wealth share by 7pp, or 47%. Homogenizing asset returns lowers the top 1% wealth share by 1pp more than in the benchmark, but lowers the top 0.1% as much as in the benchmark. The importance of bequests remains comparable. Overall, superearners remain the main driver of top wealth shares. This shows that the levels of labor income shares among top income and wealth groups required to overturn our primary conclusion are far below any margin of error attributable to the treatment of capital gains or the factor decomposition of business income.

8.3 An economy without entrepreneurs

Since a significant fraction of high-income and high-net-worth individuals are entrepreneurs, a strand of the literature has explicitly modeled entrepreneurial activity. While our framework does not feature entrepreneurs explicitly, it captures some of the key ingredients of these models, by allowing for highly productive households with varying rates of return to labor input and capital investment. In this section, we test our approach by re-calibrating our model to a world without entrepreneurs. Our objective is not to quantify entrepreneurs’ contribution to wealth concentration per se, but to test if our treatment of them (as highly productive households with potentially higher return on capital) is appropriate. If the distribution of asset returns and labor productivity among entrepreneurs were drastically different from that of other households with similar characteristics, then we would expect different roles for labor and capital in wealth concentration in this alternative calibration.

To begin, we drop entrepreneurial households from our data, and compare the distributions of earnings, income and wealth with the benchmark sample (Figure 9a). Excluding entrepreneurs lowers the concentration of net worth and earnings, but not by much. Among

Figure 9: Distribution of Wealth, Income and Earnings without Entrepreneurs

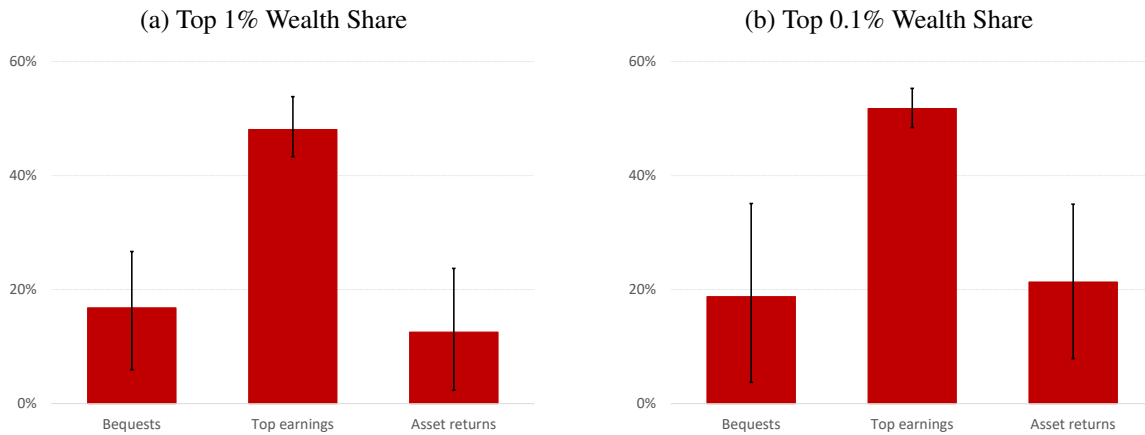


Note.— Figure shows the effect of excluding entrepreneurial households from the sample on the distributions of income, net worth and earnings. The left panel shows the marginal distributions. The right panel shows the share of net worth held by top income and earning groups. Source: SCF 2001 to 2019.

non-entrepreneurial households, the wealthiest 1% holds 31% of their combined wealth, compared to 35% among all households. This is consistent with the disproportionate prevalence of entrepreneurs among the wealthiest households. It also suggests, however, that there is considerable wealth dispersion within the rest of the population. The top 1% earnings share falls slightly from 17% to 15% when entrepreneurs are excluded. The wealth share of the top 1% of earners is 15% for non-entrepreneurs versus 19% for the population, suggesting a weaker earnings-wealth correlation (Figure 9b). Since entrepreneurs rely more heavily on capital income, labor’s income share is higher when they are excluded: 74% among the top 1% compared to 59% in the benchmark. Although labor shares are relatively homogeneous among non-entrepreneurial households, the implied dispersion in rates of return is comparable to an economy with entrepreneurs, because the net worth of top income groups is also lower when entrepreneurs are excluded from the data. For the top 0.1% (1%) of non-entrepreneurial households by income, relative rate of returns are 2.5 (1.7) times the average, compared to 2.5 (1.8) in the benchmark sample. This suggests that the larger capital income shares among high-income entrepreneurs largely reflect the size of their assets, compared to high-income, non-entrepreneurial households, although both high-income groups have higher returns on capital compared to the rest of the population.

Not surprisingly, these figures show that the earnings, income and wealth of entrepreneurs are more concentrated, and that top entrepreneurs derive less of their income from labor.

Figure 10: Factors of Wealth Concentration: An Economy without Entrepreneurs



Note.— Figure shows the marginal effect of each factor on wealth concentration among non-entrepreneurs. The whiskers show the range of effects obtained by permuting the order in which factors are eliminated from the benchmark economy. The column height represents the average across permutations.

Yet, they also show that for the economy as a whole, the presence of entrepreneurs mostly exacerbates patterns that are already present among non-entrepreneurs, notably a high concentration of earnings, income and wealth.²⁶

Figure 10 shows results for our decomposition exercise when we recalibrate the model to the “economy *sans* entrepreneurs”. The fraction of top wealth shares attributable to top earners is 48% for the top 1% wealth share and 52% for the wealthiest 0.1%, on average across simulations. These are slightly higher than 45% and 43% obtained for our baseline analysis. The fraction attributable to heterogeneous returns is smaller in the economy without entrepreneurs compared to the benchmark, explaining 13 and 21% of the top 1% and 0.1% wealth shares, compared to 17 and 29% in the baseline. The results are similar for the role of bequest heterogeneity, which explain 17 and 19% of top wealth shares, compared to 19 and 23% in the baseline analysis. These suggest that theories of concentration based on capital income and bequests are more important for entrepreneurs relative to non-entrepreneurs. However, the small difference in overall results compared to the benchmark implies that not much generality is lost by our treatment of entrepreneurs.

²⁶It is not surprising that income concentration remains high when excluding entrepreneurs. For example, Bakija et al. (2012) show that salaried executives and managers, financial professionals and similar occupations earn very large wage and salary incomes and account for a substantial fraction of top income groups.

9 Discussion

We conclude that earnings concentration is the primary driver of wealth concentration in the US, accounting for about half of the top wealth shares. The other half can be attributed to bequests and return heterogeneity. Our conclusion reflects the high empirical concentration of earnings and the large share of earnings in total income among top income and wealth groups. Yet, it may appear to be in conflict with studies that seem to suggest that the key role of earnings heterogeneity is a theoretical impossibility (Stachurski and Toda, 2019; Benhabib and Bisin, 2018).²⁷ It is important to note, however, that these theoretical results pertain to specific settings that exclude the life-cycle framework adopted here. Notably, Stachurski and Toda (2019) emphasize the necessity of infinitely lived agents for their impossibility result. In such a setting, the product of the discount factor and the gross interest rate has to be below one to ensure that aggregate wealth remains bounded. This limits the upper tail of the wealth distribution. Other factors then become necessary to generate a fat-tailed distribution, such as heterogeneity in returns or discount factors.

This is different in a life-cycle model, which allows the product of the discount factor and the interest rate to exceed one. Wealth does not grow indefinitely because, in the long run, all agents are dead. Sargent et al. (2021), in particular, show analytically that the tail of the wealth distribution can be thicker than that of earnings in a life-cycle model if agents start their lives with a low level of wealth, even with a common return on capital and a common discount factor. Inducing household wealth to grow faster than earnings – as is the case empirically – requires an equilibrium return that exceeds the discount rate by some margin. Under Sargent et al.’s (2021) assumption of random death, this gives a Pareto distribution for wealth, with a fatter tail than that of the earnings distribution. The theoretical setting we adopt, where agents enter the economy at age 20 with low wealth and expect to eventually die, shares this key feature with Sargent et al. (2021).

Dynastic economies, where agents have infinite lives and intergenerational transmission of wealth is perfect, can exaggerate the role of return heterogeneity, resulting in a counterfactually low labor share among top income and wealth groups. In Hubmer et al. (2020), for instance, we find the implied labor share of the wealthiest 1% to be too low, bounded between 6.5% and 26.2%, depending on the correlation of earnings and wealth.²⁸ This arises

²⁷Stachurski and Toda (2019), in particular, show that top wealth concentration (as measured by the thickness of the upper tail of the distribution) is bounded above by top income concentration in models of household heterogeneity with infinitely-lived agents, constant discount factors, and common, risk-free return on capital. This encompasses the seminal workhorse model of Aiyagari (1994) among others.

²⁸This can be seen from Equation (1). Defining the aggregate economy as the base group, the labor share of

because the wealthiest 1% have 27 times the average assets and enjoy higher-than-average returns on those assets, but their earnings are at most five times the average earnings in their model economy (assuming perfect correlation of earnings and wealth). As a result, their capital income swamps their labor earnings. In comparison, [Piketty and Saez \(2003\)](#) report the corresponding labor share in income as 62.5% for the wealthiest 1% in 1967, the target year in [Hubmer et al.](#)'s calibration.

Our findings also may appear to be at odds with recent quantitative analyses by [De Nardi et al. \(2016; 2020\)](#), who report that even models with rich earnings dynamics, as estimated from SSA data on individual records by [Guvenen et al. \(2021\)](#), understate top wealth concentration. Despite its rich dynamics, however, the earnings process therein significantly understates the cross-sectional earnings dispersion among households: the Gini coefficient for earnings among working age individuals is 0.41 in their calibration, much lower than the 0.56 we document for households with a working age head in the SCF.²⁹ If we re-calibrate our top earnings states to match a Gini coefficient of 0.41, which counterfactually lowers the earnings share of the highest 1% of earners to 5% from 16%, we too understate the wealth concentration, producing a Gini coefficient of 0.74 and a top 1% share of 20% in the model, versus 0.84 and 35% in the SCF respectively. Our decomposition analysis then finds a trifling role for earnings in wealth concentration (see [Figure D.1](#) in the Appendix).

The relevance of superearners for wealth concentration warrants a deeper analysis of earnings concentration. Routes of inquiry that appear promising include human capital accumulation ([Badel et al., 2020](#)), superstar effects ([Rosen, 1981](#)), labor market frictions, in particular among low earnings groups ([Ozkan et al., 2023](#)), and production complementarities or changes in the degree of assortative matching between workers and firms as well as among workers across firms ([Geerolf, 2016; Song et al., 2019](#)).

Another promising avenue is entrepreneurial activity, since earnings concentration is partly driven by entrepreneurial incomes. Recall that in the absence of credit frictions, marginal returns on business investment are equalized across entrepreneurs, and differences in entrepreneurial skill are fully reflected in earnings from the perspective of our model. This is consistent with [Bhandari and McGrattan \(2021\)](#), who find that only 26% of entrepreneurial

the wealthiest 1% is a function of their relative assets, $k_{1pct/0} = 27.4$ (from Table 1 in HKS), relative mean rates of return $r_{1pct/0} = (6.5\% + 7.2\%)/7.2\% = 1.9$ (from Figure 6 in HKS, their parameter choices, and assuming a capital-output ratio of 3), the aggregate net labor income share in HKS, $\lambda_0 = 0.78$, and their relative earnings, $e_{1pct/0}$. The latter is not reported, but it is bounded from above by the relative earnings of the top 1% earners (calculated as 5.1 from Figure 4 in HKS) – corresponding to perfect correlation of earnings and wealth – and from below by 1, which corresponds to zero correlation.

²⁹Because SSA is at the individual level whereas the SCF is at the household level, assortative household formation is one possible explanation for the discrepancy.

(human) capital is transferable upon sale of a business. Similarly, [Smith et al. \(2019\)](#) attribute three quarters of pass-through business profits to an entrepreneur-owner’s embodied human capital. Models of entrepreneurial human capital formation are promising paths for understanding how superearners emerge.

The relevance of higher returns for the wealthiest of households points to financial factors instead. Whether the wedge in rates of returns across households reflects compensation for risk or impediments to capital mobility remains an open question. While our model considered return heterogeneity for a single asset, comparing portfolio compositions of households along the wealth and income distribution could shed light on the sources of differences in asset returns.

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Online Appendix

A Entrepreneurship and the Distribution of Labor and Capital Income

Consider the following portfolio allocation problem for an entrepreneur endowed with a units of assets and a diminishing-return-to-scale business income production function $y^b = \theta k^\alpha$, where θ represents the productivity of the entrepreneur. We implicitly assume that a unit of entrepreneurial labor is supplied inelastically as long as the business is in operation. The entrepreneur's problem is to

$$\max_k y = \theta k^\alpha + r(a - k),$$

where the first term is business income and the second term is market income on excess assets (or debt service if $a < k$ in equilibrium). The optimal business investment k^* solves $\theta \alpha k^{\alpha-1} = r$. Substituting the optimality condition back into the objective function gives:

$$y^* = ra + \underbrace{(1 - \alpha)\theta_i^{\frac{1}{1-\alpha}}(r/\alpha)^{\frac{\alpha}{\alpha-1}}}_{\text{non-capital income}}$$

Note that $ra = \alpha y^b + r(a - k)$, the sum of capital's share of business income and capital income on excess assets.

This setting is observationally equivalent to a version of our model with a common return on assets and labor income heterogeneity, which here is driven by differences in entrepreneurial ability, θ . In this setting, our calibration procedure correctly interprets differences in business income as reflecting labor income heterogeneity.

Next, consider the case where entrepreneurs are constrained by their assets when investing in their business: $k \leq a$. For entrepreneurs with sufficient assets, given their productivity θ , this constraint does not bind, and the argument above applies all the same. If an entrepreneur is constrained, then the optimal investment is $k^* = a$. Let $r_i = \theta \alpha a^{\alpha-1} > r$ denote the marginal return on business capital of a constrained entrepreneur. Then total income of an entrepreneur can be written as:

$$y^* = r_i a + \underbrace{(1 - \alpha)\theta_i^{\frac{1}{1-\alpha}}(r_i/\alpha)^{\frac{\alpha}{\alpha-1}}}_{\text{non-capital income}}$$

Our accounting approach then attributes variation in the first term across households to differences in wealth and in the return on assets, and variation in the second term to differences in labor productivity. The relative shares of labor and capital income are correctly identified.

Finally note that for constrained entrepreneurs, heterogeneity in the rate of return affects not only the capital income component, but also the labor income component of income. In particular, constrained entrepreneurs have lower earnings conditional on productivity, since they cannot scale up their ideas to full capacity. Therefore, eliminating differences in asset returns also raises labor income dispersion. As a consequence, eliminating rate of return differences while keeping earnings heterogeneity unchanged, as we do in our analysis, may overstate the importance of rate of return differences. Similarly, eliminating differences in calibrated productivity levels reduces dispersion in rates of return across households, given the definition of r_i . This implies that eliminating earnings differences while keeping rate of return differences unchanged, as we do in our analysis, may understate the importance of productivity differences.

B Data Appendix

The primary sources of data are the 2001 to 2019 waves of the Survey of Consumer Finances (SCF), sponsored by the Federal Reserve Board in cooperation with the Department of the Treasury.^{A1} The measure of net worth is the difference between total assets and total liabilities, as provided by the SCF. To compute total market income, we sum wage and salary income, business and farm income, interest and dividend income, private pension withdrawals and capital gains. Some tables exclude capital gains from income, as explained in the text and in the table notes. Income from fiscal sources, such as transfer income or Social Security income, is excluded.

Wage shares reported in the tables represent wage and salary income divided by total market income. The labor income share reported in the tables additionally includes part of business and farm income for a subset of households. The SCF distinguishes between business income from an actively managed business or farm and that from non-actively owned businesses. Specifically, we impute wage income in two situations: first, when the entire household reports no wage and salary income at all, but reports a positive income from an actively managed business or farm and positive equity invested in an active business; second,

^{A1}The public use data files are available for download at <https://www.federalreserve.gov/econres/scf-previous-surveys.htm>.

when the respondent (R) or their spouse (SP) reports active business income, reports self-employment as their main job *and* reports not having drawn any wage and salary income from their business. Importantly, we do not modify any wage and salary income reported to the SCF by active business owners. Households in the imputed sample constitute 15% of the sample, representing 9% of the population and roughly half the households with active business investment.

Our imputation sample also excludes situations where active involvement in the business is not the main job of the respondent or their spouse. It also excludes other members of the household, e.g., children who are actively involved in the business but do not report wage or salary income. Therefore, our measure of labor’s share of income likely understates the true labor share.

Most of the households with imputed wages do not belong to the top income or wealth groups. Of all the households in our imputation sample, 3% belong to the top 1% income group and 4% belong to the wealthiest 1% of the population. 95% belong in neither top group. These are better odds than in the general population. Consequently, roughly a quarter of the households in the top 1% income or wealth group have some imputed wages.

To estimate the capital share of business income we regress active business income on the equity invested in the business among households that report no wage and salary income, but report a positive income from an actively managed business or farm, our main imputation sample.^{A2} The regression specification is:

$$\ln Y_i = cons. + \alpha \ln K_i + \beta \ln L_i + \epsilon_i,$$

where Y_i is the household’s total income from the business, K_i is equity invested in the business and L_i is the effective labor input, including hours of work as well human capital or entrepreneurial acumen.^{A3} The implicit assumption behind this regression is that the investment income from the business is distributed in proportion to the equity of the shareholders, so that the capital component of business income is αY_i . The SCF reports active business equity, which we include as K_i . The effective labor input, L_i , is not directly observed. To control for the labor input, we include the following variables as controls: indicators for categories of educational attainment, age, race, gender, major occupation category, survey

^{A2}We exclude households from the regression sample if anyone other than the respondent or their spouse is actively involved in the business since hours worked for the business is only available for R and SP.

^{A3}To account for negative values of business income, we use the following logarithmic transformation: $\widetilde{\log x} = sign(x) \times \log(1 + |x|)$.

year interacted with educational attainment and occupation, and (log) total hours worked by the respondent and their spouse for the business, interacted with educational attainment and occupation. These variables capture the quantity of labor input with hours worked and the quality of the labor input with demographic variables as well as education and occupation. The estimated value of α is 0.25 (s.e. 0.03), which is what we use to apportion business income into its capital and labor components.^{A4}

Table B.1: Labor Component of Income by Income and Wealth Group

Income Percentile	99-100	99.9-100	99.5-99.9	99-99.5	95-99	90-95	0-100
Wage Income							
with capital gains	0.44	0.30	0.47	0.60	0.67	0.84	0.74
without capital gains	0.54	0.44	0.54	0.66	0.71	0.86	0.78
Labor Income							
with capital gains	0.53	0.39	0.57	0.69	0.75	0.88	0.80
without capital gains	0.66	0.58	0.66	0.75	0.79	0.90	0.84
Net Worth Percentile	99-100	99.9-100	99.5-99.9	99-99.5	95-99	90-95	0-100
Wage Income							
with capital gains	0.35	0.21	0.36	0.46	0.58	0.72	0.74
without capital gains	0.44	0.27	0.46	0.56	0.62	0.75	0.78
Labor Income							
with capital gains	0.45	0.31	0.46	0.56	0.68	0.79	0.80
without capital gains	0.56	0.41	0.58	0.68	0.73	0.82	0.84

Note.— Table shows wage and labor shares of total income by percentiles of the income and net worth distribution. Labor income includes imputed wage income for active business owners who do not draw salary from their businesses. Source: SCF 2001 – 2019

Table B.1 shows the values for the wage and labor components of income (for different income and net worth groups) that are used to plot Figure 1. Table B.2 compares our findings with statistics from IRS data. We use the 2018 update to the tables in Piketty and Saez (2003), who report the sources of income for finely defined top income groups. Since it is not possible to observe which tax units draw a salary from their business, no imputation is made, and we report business income separately. These figures are comparable to the top

^{A4}As is common in the literature, we use the demographic measures, educational attainment and occupation of the head of the household since details are not available for each member of the household who actively participates in the business.

Table B.2: Composition of Income for Top Income Groups (IRS)

without capital gains	Income Percentile Category				
	99-100	99-99.5	99.5-99.9	99.9-99.99	99.99-100
Wage	57	72	61	48	39
Business	29	20	29	36	35
Interest and Dividend	14	8	11	15	26

with capital gains	Income Percentile Category				
	99-100	99-99.5	99.5-99.9	99.9-99.99	99.99-100
Wage	48	66	53	39	31
Business	25	18	25	29	28
Int., Div. and Capital Gains	27	16	22	31	42

Note.— Figures in percentages and correspond to averages for 2000-2018. Income percentiles are determined excluding capital gains (KG). Figures come from 2018 data update to [Piketty and Saez \(2003\)](#).

rows of Figure 1. The share of wage income for the top 1 percent income group as reported by tax units in Table B.2 is 48 percent when capital gains are included, and 57 percent when they are excluded – slightly above our findings in the SCF data reported in Table B.1.^{A5} Columns 2 to 5 in Table B.2 report the components of income within the top 1 percent of income. Wage income constitutes more than half the income for those outside the top 0.1 percent of top income earners. For the top 0.1 percent of the income distribution, the share of wage income drops and interest and dividend income becomes increasingly important. For the top 0.01 percent of the income distribution, interest and dividend income constitutes 42 percent of total income when capital gains are included.

Both the survey data from the SCF and the tax data from the IRS records agree on the relative roles of sources of income. For most households, earned income from labor services is the primary source of income. As we move up the income ladder, the share of labor income declines, and income from capital increases. Nonetheless, even among the top 1% of households (and tax units), the most conservative definition of labor income indicates that at least about half the income can be attributed to labor. As the size of the top fractile is

^{A5}There are two subtle but apparently inconsequential differences between the two sets of statistics. First, the income concept reported in [Piketty and Saez \(2003\)](#) includes fiscal income, such as Social Security payments and other transfer payments. Since transfer payments are not a significant source of income for top income groups, this does not affect the results. Second, the IRS data are based on tax units, whereas the SCF data are based on primary economic unit, which consists of the core members of the household. In most cases, this includes the respondent, their spouse, if any, and their dependent children.

reduced, capital income becomes more important. The upshot of this is that labor income remains a non-negligible source of income throughout, and is a primary source of income for most households (or tax units) outside the highest income and net worth groups.

C Details of Model Calibration

C.1 Demographics

Following [Halliday et al. \(2019\)](#), we model survival probability as a logistic function of age: $s(j) = [1 + \exp(\omega_0 + \omega_1 j + \omega_2 j^2)]^{-1}$ and use their recommended parameter values. [Halliday et al. \(2019\)](#) calibrate to three moment conditions: the dependency ratio (population aged 65 and over divided by population aged 20-64), which is 39.7% in the data; the age-weighted death rate for 20 to 100 year olds of 8.24%, and the ratio of the change in the survival probability between ages 65-69 and 75-79 to the change in survival probability between ages 55-59 and 65-69, which is 2.27 in the data.

C.2 US Personal Income Tax System

Taxable personal income is given by:

$$y_f = (zw\varepsilon_j h) \mathbb{I}_{j < J_r} + b(z) \mathbb{I}_{j \geq J_r} + \min\{r\kappa k, d_c\},$$

where $\mathbb{I}_{j \geq J_r} \in \{0, 1\}$ indicates retirement status. Disposable income is obtained by deducting corporate and personal income taxes and adding transfers:

$$y^d = \lambda \min\{y_b, y_f\}^{1-\tau} + (1 - \tau_{max}) \max\{0, y_f - y_b\} + (1 - \tau_c) \max(r\kappa k - d_c, 0) + Tr$$

The first two terms above represent our formulation of the current US income tax system, which can be approximated by a log-linear form for income levels outside the top of the income distribution ([Bénabou, 2002](#)), augmented by a flat rate for the top income tax bracket. The power parameter $\tau \in [0, 1]$ controls the degree of progressivity of the tax system, while λ adjusts to meet the government's budget requirement.

The second term caps the marginal tax rate at $\tau_{max} = 39.6\%$, as reported by the IRS. y_b denotes the critical level of taxable income at which the top marginal tax rate is reached: $\lambda(1 - \tau)y_b^{-\tau} = 1 - \tau_{max}$. We calibrate the progressivity of the income tax system, τ , to the

difference between the average income tax rate paid by the top 1% and the bottom 99% of the income distribution. [Piketty and Saez \(2007\)](#) report this value to be 12.4%.

C.3 Pension Benefits

The formula that determines Social Security benefits features two bend points (bp_1 and bp_2 expressed as multiples of average earnings), three replacement rate brackets (0.90, 0.32, and 0.15), and a maximum benefit, b^{cap} . The benefit for an individual retiring with productivity z is

$$b(z) = \xi \min\{b^{cap}, 0.9 \min(\tilde{e}(z), bp_1) + 0.32 \max[\min(\tilde{e}(z), bp_2) - bp_1, 0] + 0.15 \max(\tilde{e}(z) - bp_2, 0)\},$$

where $\tilde{e}(z)$ are average earnings of working age agents of productivity z in the model's stationary equilibrium. The formula reported by the SSA is for an individual, whereas the model is based on households, which may contain non-working spouses or survivors. Therefore, we adjust benefits by a factor, ξ , and calibrate it to match the average ratio of Social Security expenditure to GDP in the data.

C.4 Labor Productivity Process

Table [C.1](#) summarizes the transition probabilities and the corresponding productivity levels for the stochastic process. The initial distribution represents the share of workers in each productivity state at labor market entry. Since the initial distribution of young workers is different from the invariant distribution, and because agents have finite lives, the population shares of workers across productivity states are different from the invariant distribution. The population shares for the working age population are reported in the last row of the table. Retired agents have zero labor productivity.

Note that our formulation implies that if a household loses its extraordinary status, then it is equally likely to transition to any one of the ordinary states. The effect of this assumption on our quantitative analysis is negligible. In particular, assuming instead that all those leaving z_7 downwards enter z_6 hardly affects our quantitative findings.

Table C.1: Calibrated Productivity Process in the Benchmark Economy

	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8
$z_1 = 1.00$	0.874	0.119	0.004	0	0	0	0.002	0
$z_2 = 2.05$	0.060	0.878	0.060	0	0	0	0.002	0
$z_3 = 4.21$	0.004	0.119	0.874	0	0	0	0.002	0
$z_4 = 3.47$	0	0	0	0.874	0.119	0.004	0.002	0
$z_5 = 7.12$	0	0	0	0.060	0.878	0.060	0.002	0
$z_6 = 14.59$	0	0	0	0.004	0.119	0.874	0.002	0
$z_7 = 124.83$	0.021	0.021	0.021	0.021	0.021	0.021	0.850	0.021
$z_8 = 1034.51$	0	0	0	0	0	0	0.242	0.758
initial distribution	0.044	0.412	0.044	0.044	0.412	0.044	0	0
population share	0.098	0.300	0.098	0.098	0.300	0.098	0.0081	0.0004

Notes.— Table shows the calibrated productivity levels and the corresponding transition probabilities. The last row shows the fraction of working age population in each productivity state.

C.5 Stochastic Process for Rates of Return

Table C.2 summarizes the transition probabilities and the corresponding annualized rates of return for the stochastic return process.

C.6 Calibration Approach

Our calibration aims to minimize the equally weighted sum of squared deviations between model moments and data moments.

The age-wealth profile enters our calibration objective function as the mean squared distance between wealth by age group in the model and in data.

Note that in computing model measures of intergenerational wealth persistence, we exclude model parent-child pairs where either the child or the parent is in the top 1% of wealth. Results are similar when they are included.

C.7 Summary Tables

Table C.3 shows the preset parameters. Table C.4 shows the values for internally (and jointly) calibrated parameters. Table C.5 shows a summary list of calibration targets along with their sources and the associated values obtained in the benchmark economy.

Table C.2: The Transition Matrix for Rates of Return on Capital

from / to	κ_L	κ_H	κ_{top}
κ_L	0.96	$0.04 - \pi_{in}(z)$	π_{in}
κ_H	$0.06 - \pi_{in}(z)$	0.94	$\pi_{in}(z)$
κ_{top}	0.0	0.10	0.90
population share (%)	59.9	40.0	0.1
annual rate of return (%)	0.0	6.7	22.7

Probability of entering the top return state by z state of origin:

	z_1 to z_6	z_7	z_8
$\pi_{in}(z)$	2.5×10^{-4}	1.3×10^{-3}	3.8×10^{-3}

Note.— The top panel shows the transition probabilities in the benchmark economy from the rate of return in Column 1 to rates of return in Columns 2 to 4. The annual rates of return associated with each state and the share of the population in each state are reported in the last two rows. Transition probabilities vary with the state z , as shown in the lower panel.

Table C.3: Calibration of the Model: Preset Parameters

Parameter	Description	Value	Source
<i>Demographics</i>			
J	Maximum life span	16	corresponds to age 100
J_R	Mandatory retirement age	10	corresponds to age 65
$\omega_0, \omega_1, \omega_2$	Survival probability by age	-5.49, 0.15, 0.016	Halliday et al. (2019)
<i>Preferences</i>			
σ_c	Risk aversion	1.5	
σ_l	Inverse Frisch elasticity	1.22	Blundell et al. (2016)
<i>Technology</i>			
δ	Depreciation (annual)	0.045	
<i>Labor productivity</i>			
See Sections 5.3 and C.4			
<i>Taxes and transfers</i>			
τ_c	Marginal corporate tax rate	0.236	Gravelle (2014)
τ_s	Consumption tax rate	0.05	Kindermann and Krueger (2022)
Tr	Government transfers/GDP	2.7%	NIPA Table 3.12

Table C.4: Calibration of the Model: Jointly Calibrated Parameters

Parameter	Description	Value	Parameter	Description	Value
β	Annual Discount rate	0.974	θ	Labor disutility	6.0
α	Capital elasticity	0.27	$\lambda_{in}, \lambda_{ll}, \lambda_{lh}, \lambda_{hh}$	Transition rates	Table C.1
z_7, z_8	Top productivity states	Table C.1	$\pi_{ll}, \pi_{hh}, \pi_{in}, \pi_{top, top}$	Transition rates	Table C.2
$\kappa_L, \kappa_H, \kappa_{top}$	Rates of return	Table C.2	d_c	Corporate asset threshold	2.21
τ_l	Tax progressivity	0.17	G/Y	Expenditures / GDP	11.6%
ξ	Pension / Earnings	0.62	$\tilde{\gamma}_z, \tilde{\gamma}_\kappa$	Bequest correlations	0.65, 0.9
ϕ_1, ϕ_2, σ_b	Bequest utility	-1.4, 0.1, 1.35			

Table C.5: Summary of Target Moments

Moment	Source	Data Value	Model Fit	Moment	Source	Data Value	Model Fit
Mean hours worked	SCF 2001–2019	0.35	0.34	Soc. Sec. Pay / GDP	NIPA	7.9%	8.1%
Top 0.1%, 1% earning shares	SCF 2001–2019	Figure 3	Figure 3	Probability of staying in top 1% earners	Kopeczuk et al. (2010)	0.62	0.64
Top 0.1%, 1%, 5%, 10% wealth shares	SCF 2010–2019	Figure 3	Figure 3	Log wealth correlation between parents and kids	Charles and Hurst (2003)	0.37	0.39
Bequest/Wealth	Güvönen et al. (2023)	~ 1%	2%	Top 2% bequest dist.	Feiveson and Sabelhaus (2018)	40%	39%
Age-Wealth profile	SCF 2001–2019	Figure 5c	Figure 5c	Corporate income tax revenue/GDP	NIPA	2.5%	2.3%
Difference between average income tax rate for top 1% and 99%	Piketty and Saez (2007)	12.4%	13.0%	Top 0.1% labor income share	SCF 2010–2019	0.49	0.49
Overall labor income share	SCF 2010–2019	0.82	0.79	Top 10% labor income share	SCF 2010–2019	0.72	0.71
Top 1% labor income share	SCF 2010–2019	0.59	0.59	Intergenerational wealth persistence at 4th quintile	Charles and Hurst (2003)	0.36	0.32
Intergenerational wealth persistence at 4th quintile	Charles and Hurst (2003)	0.26	0.22	Mean return top 0.1% income / mean	SCF 2001–2019	1.8	1.6
Mean return top 0.1% income / mean	SCF 2001–2019	2.5	2.0	Mean return top 1% wealth / mean	SCF 2001–2019	1.2	1.2
Mean return top 0.1% wealth / mean	SCF 2001–2019	1.3	1.5				

D Supplementary Tables and Results

Table D.1 shows additional decomposition results for wealth concentration. The first row reports the benchmark results. Row (1a) removes non-homotheticity in altruism by setting $\phi_2 = 0$, which makes bequests proportional to wealth. In (1b), we remove the correlation of bequests with parental wealth by setting both $\bar{\gamma}_z$ and $\bar{\gamma}_\kappa$ to 0.5, so that all bequest recipients draw their bequest from the same distribution. While this eliminates the intergenerational correlation of wealth, its effect on top wealth concentration is modest, with top wealth shares decreasing by about 10 percent. In row (1c), we set σ_b equal to σ_c . Out of the three scenarios in this table, this one has the strongest effect on wealth inequality. Nevertheless, its effect (necessarily) is much weaker than that of fully equalizing bequests, as considered in the main text.

In (2), we set the value of the higher top productivity state, z_8 , equal to the calibrated value for the lower top state, z_7 . This lowers wealth concentration by about 10 percent for the top 1% and about a quarter for the top 0.1%.

In (3), we set the top excess return, κ_{top} , equal to the higher regular excess return, κ_H . This cuts the top 0.1% wealth share by about a half and the top 1% wealth share by about a fifth.

D.1 Sensitivity to Labor Share Estimates

In Section 8.2, we calibrated the model to wage shares instead of labor income shares, that is, we allocated all business income to capital. The low LIS economy differs from the benchmark not only in lower top LIS (49% instead of 59% for the top 1% income group and 37% instead of 49% for the top 0.1% group), but also has lower earnings concentration and slightly lower relative rates of return at the top. To match these statistics, we recalibrate key parameters of the model. Because the aggregate *wage* income share is lower than the labor income share, we target the top LIS relative to the aggregate one.

Here, we report the main changes in parameters. The low-LIS economy has different top productivity parameters (z_7 is 24% lower than in the benchmark, z_8 is 9% higher), and substantially greater return dispersion. The low (medium) [high] return is 0.1% (7.7%) [24.4%]. In addition, the bequest parameter ϕ_1 is lower in absolute value, at -0.45.

Table D.2 shows the main decomposition results for this economy. All results are summarized in Figure 8 in the main text.

Table D.1: Determinants of Wealth Concentration: Additional Decomposition Results

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
... (0) benchmark	0.80	0.15	0.35	0.050	0.16
<i>counterfactual economies with ...</i>					
... (1a) homothetic bequests	0.78	0.15	0.34	0.050	0.16
... (1b) uncorrelated bequests	0.80	0.13	0.33	0.050	0.16
... (1c) $\sigma_b = \sigma_c$	0.77	0.11	0.30	0.049	0.16
... (2) $z_8 = z_7$	0.79	0.11	0.31	0.028	0.14
... (3) $\kappa_{\text{top}} = \kappa_H$	0.79	0.09	0.28	0.050	0.16

Note.— Results from model simulations. In counterfactual economy (1a), we set ϕ_2 to zero, making the bequest motive homothetic. In (1b), we remove the correlation of bequests with parental wealth by setting both $\bar{\gamma}_z$ and $\bar{\gamma}_\kappa$ to 0.5, so that all bequest recipients draw their bequest from the same distribution. In (2), we set the value of the higher top productivity state, z_8 , equal to the calibrated value for the lower top state, z_7 . In (3), we set the top excess return, κ_{top} , equal to the higher regular excess return, κ_H . In (4), we do not allow top earners to transit into the top return state.

D.2 An Economy with Low Earnings Concentration

Figure D.1 and Table D.3 show decomposition results for an economy with a counterfactually low earnings inequality, as discussed in Section 9 in the main text. In particular, we recalibrate the earnings process in our model by setting the two top productivity states z_7 and z_8 to a common value that implies an earnings Gini of 0.41 as in De Nardi et al. (2016). This change also implies a reduction in the top 1% (0.1%) earnings share to 5% (1%), much below the data value of 17% (6%), which our benchmark model matches closely. The recalibrated model with low earnings inequality also has much lower wealth concentration, with a wealth Gini of 0.74 and a top 1% wealth share of 20%. This Gini coefficient is close to that found by Huggett (1996), and by De Nardi et al. (2016) when using an AR(1) process for earnings. In this economy, further reducing top earnings by setting z_7 and z_8 to equal the top ordinary productivity state, z_6 , hardly reduces wealth inequality. This is not surprising, since the gap between top and ordinary productivity is small in this low-earnings-inequality economy. Instead, heterogeneous returns have a major effect on wealth concentration. Eliminating them reduces top wealth shares dramatically, and takes them to levels similar to those obtained in the models of Huggett (1996) and De Nardi et al. (2016; 2020), with a top 1% wealth share

Table D.2: Determinants of Wealth Concentration: Excluding Imputed Wages for Entrepreneurs

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
benchmark	0.83	0.15	0.34	0.05	0.14
<i>Counterfactual economies with ...</i>					
... (1) equal bequests	0.75	0.10	0.25	0.05	0.14
... (2) no top earners	0.77	0.08	0.20	0.005	0.04
... (3) common returns	0.75	0.09	0.26	0.05	0.14

Note.— Results from model simulations, for a calibration targeting lower top labor income shares (see text). Economy (2) sets the extraordinary productivity levels to that of the highest “regular” earnings category ($z_8 = z_7 = z_6$). Economy (3) sets κ to its value-weighted average in the benchmark economy.

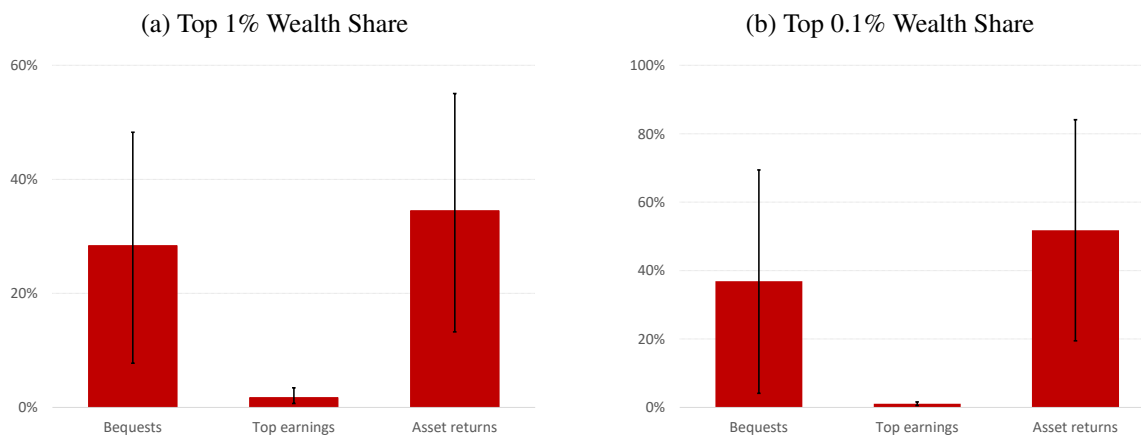
of about 10%.

Table D.3: Determinants of Wealth Concentration – Alternative Economy with Low Earnings Inequality

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
data	0.84	0.13	0.35	0.06	0.17
benchmark	0.80	0.15	0.35	0.05	0.16
<i>Alternative economy with earnings Gini = 0.41</i>					
	0.74	0.08	0.20	0.01	0.05
<i>Counterfactual economies with low earnings inequality and ...</i>					
... (1) equal bequests	0.67	0.03	0.10	0.01	0.05
... (2) no top earners	0.74	0.08	0.20	0.004	0.04
... (3) common returns	0.66	0.01	0.09	0.01	0.05

Note.— The alternative economy has the same parameters as the benchmark, except that the top productivity levels z_7 and z_8 are equal and set to generate a Gini coefficient of earnings of 0.41. Counterfactual economies are generated as in Table 5 in the main text.

Figure D.1: Factors of Wealth Concentration – Alternative Economy with Low Earnings Inequality



Note.— Figure shows the marginal contribution of each factor to the concentration of net worth relative to the alternative economy with low earnings concentration. The whiskers show the range of marginal effects obtained by permuting the order in which factors are eliminated from the benchmark economy. The column height represents the average across permutations.