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 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, but much less for the rest.

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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 the economy's balance. Economists have given 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; and bequests.

These explanations differ in their depictions of who the wealthy are and how they become wealthy. As a result, they disagree in their assessments of economic policy.[1] Regrettably, a direct empirical assessment of how important labor and capital income are for building large fortunes in the US is infeasible due to the lack of long panel data on earnings, assets and their returns for households at the top of the income and wealth distribution. In this paper, we combine cross-sectional data on the joint distribution of net worth, earnings and income with an overlapping-generations model of savings to assess the relevance of the different modeling approaches to wealth concentration.

The key difference between the different explanations, which our analysis exploits, is their prediction for the factor composition of income among top income and wealth groups. If wealth concentration is driven by differences in asset returns (or bequests), then these groups should rely heavily on capital income. If it is driven instead by earnings differences, then labor income should be the primary source of income. 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. This suggests an indispensable role for earnings in shaping the wealth distribution.

The somewhat lower labor income shares among the highest income and wealth groups nonetheless reflect the relative importance of capital income for these groups. Our calculations indicate that the low shares among the wealthiest are mostly explained by their large stocks of wealth rather than differences in rates of return.[2] By contrast, we find siz-

[1] For 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. (2019) 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.

[2] Saez and Zucman (2016) reach a similar conclusion using administrative tax data.

able differences in asset returns across income groups. The effect of these differences on wealth concentration depends on variations in income and on fluctuations in the rates of returns themselves over the course of a lifetime. But such dynamics cannot be estimated from cross-sectional data. We discipline these dynamics by requiring them to be consistent with the joint cross-sectional distributions of earnings, capital income and wealth in a structural model of wealth formation. The emphasis on joint distributions is key to our approach relative to the macro literature on wealth distribution, which has focused exclusively on marginal distributions of income and wealth.

To that end, we employ a general equilibrium, life-cycle model of household saving behavior. The model features uninsurable shocks to earnings and rates of return, a non-homothetic bequest motive, survival risk and retirement. These elements capture the three main motives for saving: the precautionary motive, the life cycle motive, and the bequest motive. We then calibrate the model to match the joint cross-sectional distribution of earnings, income and net worth, including top labor income shares and rates of return. When combined with our model of savings, these distributions are informative of the dynamics of the rates of return on assets and top incomes. The calibrated model features realistic earnings dispersion and leptokurtic dynamics with negative skewness as documented by Guvenen et al. (2021), as well as realistic correlations between rates of return, income and wealth. It also accurately depicts the life-cycle profiles of earnings, income and wealth, as well as their cross-sectional dispersions by age group.

We assess the relative contributions of the model components to wealth concentration by removing them in various combinations and examining the changes to the wealth distribution. Eliminating the highest wage earners induces the largest drop in top wealth shares on average, by about half, with little sensitivity to the presence of other factors. Eliminating bequest inequality reduces them modestly, by ten to twenty percent. Eliminating the dispersion in rates of capital return mostly affects the wealthiest 0.1%, reducing their share in wealth by 13 to 63 percent, with an average across combinations of 36 percent. Other concentration measures and the Gini coefficient are affected less. Return heterogeneity has a smaller effect in counterfactual economies with equal bequests, revealing complementarity between the roles of bequests and capital returns in explaining wealth concentration. Therefore, even though bequests explain less than a fifth of top wealth shares alone, they matter more indirectly, by amplifying the effects of return heterogeneity.

Overall, we find the concentration of labor earnings to be the primary source of wealth dispersion in the US. This puts the emphasis on theories of earnings concentration, including human capital, superstars or entrepreneurial acumen. Our findings reflect the importance of labor earnings for top income and wealth groups in the data. They are robust to measurement concerns, as earnings remain the primary source of wealth concentration even in a calibration with substantially lower top labor income shares, despite a slightly larger role for return heterogeneity.[3] In contrast, models that rely on asset returns and bequest motives alone to generate the empirical wealth concentration not only severely understate earnings concentration but also imply labor shares in income among top income and wealth groups that are far below plausible lower bounds.

Return heterogeneity and bequest inequality play significant but secondary roles. This is driven by the slow transitional dynamics of models with rate of return heterogeneity (Gabaix et al., 2016) and the life-cycle setting. Because young people hold little wealth in the data, differences in capital returns do not manifest in wealth concentration until much later, and their effect is limited by the length of life. Bequests help perpetuate wealth accumulation of dynasties by effectively extending that horizon, but this mechanism is modest given the intergenerational wealth correlation in the data. Nonetheless, bequests and return heterogeneity together explain the remaining half of wealth concentration, especially among the highest echelons of wealth.

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 the 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 Imrohoroğlu (1989), Huggett (1993) and Aiyagari (1994). In this setting, dispersion in asset holdings emerges from households' motives to accumulate assets in order to insure themselves against earnings fluctuations. Early iterations of these mod-

[3] They are mostly unchanged when calibrating the model to data excluding entrepreneurs, suggesting similar determinants of wealth concentration among non-entrepreneurs and in the general population.

els focused on the implications of household heterogeneity for macroeconomic outcomes, such as the role of precautionary savings for total capital accumulation. It was nonetheless noted that the observed differences in earnings and income risk, as measured in household surveys (e.g. the PSID), were not large enough to generate a highly skewed distribution of wealth. 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 modelling extensions.[4]

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 modelling 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 earn-

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

ings levels 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 who 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 in 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 entrepreneurial income to primarily reflect 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 modelling 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 lack of data on the dispersion and persistence of rates of return on assets at the household level in the US.[5] Our analysis fills this gap.

[5] Recent 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. Our definition of 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 market income from labor and from capital. Labor income consists of wage and salary income, which includes pay for work for an employer as well as any salary drawn from an actively managed business. The vast majority of households report these explicitly in the SCF. For corporations, the IRS requires actively involved shareholders to explicitly report their salaries. 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 wages 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 does not change the conclusions we draw from the empirical patterns below, reported with and without imputed salaries. For our benchmark analysis, we include imputed wages in labor income and later present a version without imputed wages for robustness.

To determine the share of business income that is attributable to capital, we assume that the contribution of capital to active business income is proportional to the total value of equity held in the business. Consequently, we regress active business income on business equity, controlling for the quantity and quality of the labor input. Specifically, we include the number of hours worked by the household members that 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.[6] 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 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', that 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

[6] This 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[†]

[†] 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: Authors' calculations from SCF 2001 – 2019.

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 more skewed than the total (realized and accrued) capital gains.[7]

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.

[7] In any case, any bias is likely to be small since Larrimore et al. (2021) report that unrealized gains are only 3.3% of income excluding capital gains (see Table 3 therein).

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: Author's calculations from SCF 2001 – 2019.

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 the households. The red solid bars show the labor share of total income, including imputed earnings for those 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.[8] 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.

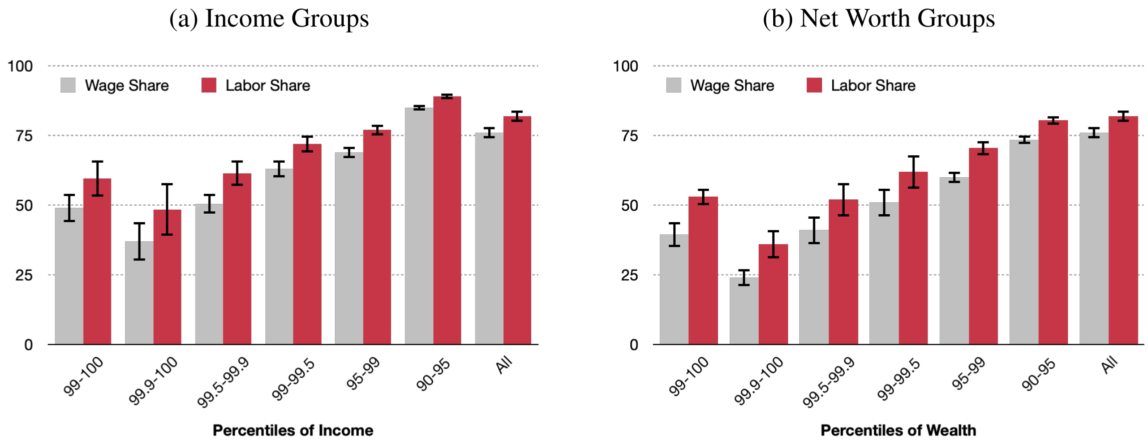
For the top 1% of the income distribution, labor income constitutes 53% of total income when capital gains are included, and 66% when they are excluded. The wage share, which excludes imputed wages for some proprietors, is roughly 10 points lower. Columns 2 to 4 show the percentiles of income within 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 0.50 and 0.56, 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 data based on tax returns (see Table

[8]Since 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 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. Author's calculations from SCF 2001 – 2019.

B.2). Both data agree on the relative roles 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 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.

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:[9]

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

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

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

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 3.9% ($= \sum_i k_i r_i$) per year, which corresponds to the rate in our quantitative analysis below. Using our preferred labor share measure, the dark columns show an annual rate of return of 2.2% for the base income group, with higher rates up along the income ladder. The average return for the top 1% of incomes is 6.8%, and it is 9.7% 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 (corresponding to gray bars in Figure 1). The estimated rates of return rise from 2.4% for the base group to 8.8% for the highest income group.

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

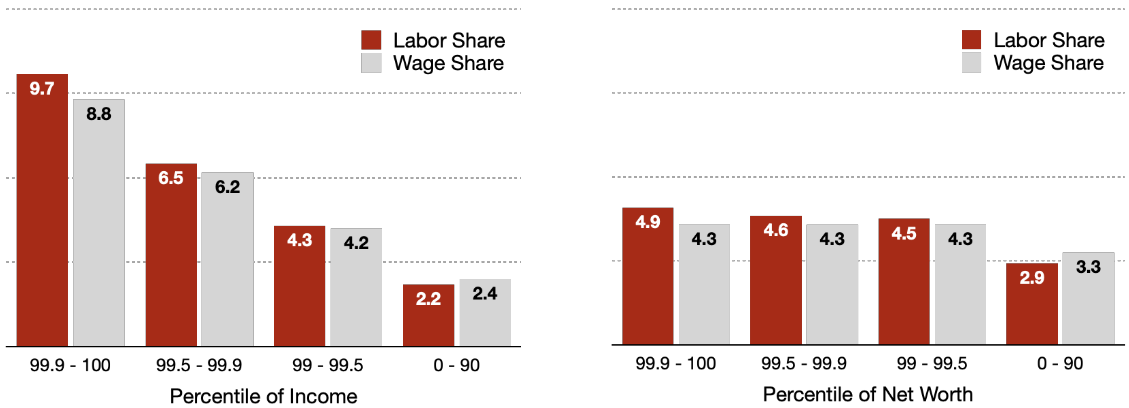
While Figure 2 suggests a modest degree of *cross-sectional* heterogeneity in asset returns, it is not possible to accurately gauge how much this matters for wealth concentration. Since higher rates of return lead to higher income and, ultimately, higher wealth, the positive

[9] $\lambda_i = \frac{e_{i/0}e_0}{e_{i/0}e_0 + r_i k_{i/0} k_0} = \frac{e_0}{e_0 + \frac{k_{i/0}}{e_{i/0}} r_i k_0} = \frac{e_0}{e_0 + r k_0} \frac{e_0 + r k_0}{e_0 + \frac{k_{i/0}}{e_{i/0}} \frac{r_i}{r_0} r_0 k_0} = \frac{\lambda_0}{\lambda_0 + \frac{k_{i/0}}{e_{i/0}} \frac{r_i}{r_0}(1-\lambda_0)}$.

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

(a) Income Groups

(b) Net Worth Groups



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 3.9%. Labor share includes imputed wage income for active business owners who do not draw salary from their businesses, whereas wage share excludes it (see Figure 1). Author's calculations from SCF 2001 – 2019.

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 saving 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 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 earning 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 $wz\varepsilon_j h$, 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.[10] Total income is denoted by y.

All income is subject to taxation. 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 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: $Y = F(K, N) = \Psi K^\alpha N^{1-\alpha}$. 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 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

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

[10] The 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 pensions system while maintaining computational feasibility.

subject to

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

where $\phi(k) = \phi_1\left[(k+\phi_2)^{1-\sigma_c} - 1\right]$ is the utility value of bequeathed assets, and $\Phi(j,z,\kappa)$ denotes assets received as a bequest. The expectation is taken over the future values of the labor endowment, z', and the rate of return on assets, κ', given the processes F_z and F_κ.

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

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

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, (iii) factor markets clear:

$$K = \int k'(s)d\mathit{\Gamma}(s) \qquad N = \int z\varepsilon_j h(s)d\mathit{\Gamma}_{j<J_r}(s),$$

the government's budget is balanced:

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

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, wealth and income, as well as other informative data moments.[11] Below, we describe our calibration strategy and highlight the key assumptions. A full list of calibration results, including target moments and parameter values, are reported 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 earning 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 age $J = 16$ (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.[12]

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: ϕ_1 and ϕ_2. We discuss the last two 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, Pistaferri and Saporta-Eksten (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 3.2 given an annual depreciation rate of 4.5%. This results in a value of $\beta = 0.945$ (0.989 per annum). The implied (value-

[11] Specifically, we minimize the equally weighted sum of squared deviations between model moments and data moments.

[12] 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.

weighted) interest rate that clears the asset market is 3.9%. We normalize the equilibrium wage rate, $w = 1$, which requires an aggregate TFP of $\Psi = 1.55$. We set capital's share in output to $\alpha = 0.27$, to match 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 in 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 their extraordinary status, then it is equally likely to transition to any one of the ordinary states.[13]

Our working assumption is that the values for the ordinary states and the transitions among them can be inferred from survey data, whereas the transitions to, from and among extraordinary states can not. 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 reflect differences in the permanent component, and the remaining 40% reflect 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

[13]The effect of these assumptions on our quantitative analysis is negligible. In particular, assuming instead that those leaving z_7 downwards all enter z_6 hardly affects our quantitative findings.

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.

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 percentile groups 95-99, 99-99.9 and 99.9-100 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. We calibrate this profile to that from the PSID.

5.4 Rate of return process

The rate of retun on capital is stochastic and takes three values, $\{r\kappa_L, r\kappa_H, r\kappa_{top}\}$, where r is the equilibrium market 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:

$$\Pi_\kappa(z) = \left(\begin{array}{c|ccc} & \kappa_L & \kappa_H & \kappa_{\text{top}} \\ \hline \kappa_L & \pi_{ll} & 1-\pi_{ll}-\pi_{in}(z) & \pi_{in}(z) \\ \kappa_H & 1-\pi_{hh}-\pi_{in}(z) & \pi_{hh} & \pi_{in}(z) \\ \kappa_{\text{top}} & 0 & 1-\pi_{top,top} & \pi_{top,top} \end{array}\right)$$

We assume that $\pi_{in}(z)$ is identical for ordinary productivity levels $(z_1, .., z_6)$ 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 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 earners relative to the bottom 90 percent, 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.[14]

5.5 Tax and transfer system

Taxes are levied on personal income, corporate income and sales 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

[14]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.

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%.[15] We calibrate the progressivity of 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.

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).

5.6 Bequests

The utility value of bequests is $\phi(k) = \phi_1[(k + \phi_2)^{1-\sigma_c} - 1]$, 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. (2019) and the share of the largest 2% of bequests in total bequests, which is 40% (Feiveson and Sabelhaus, 2018).

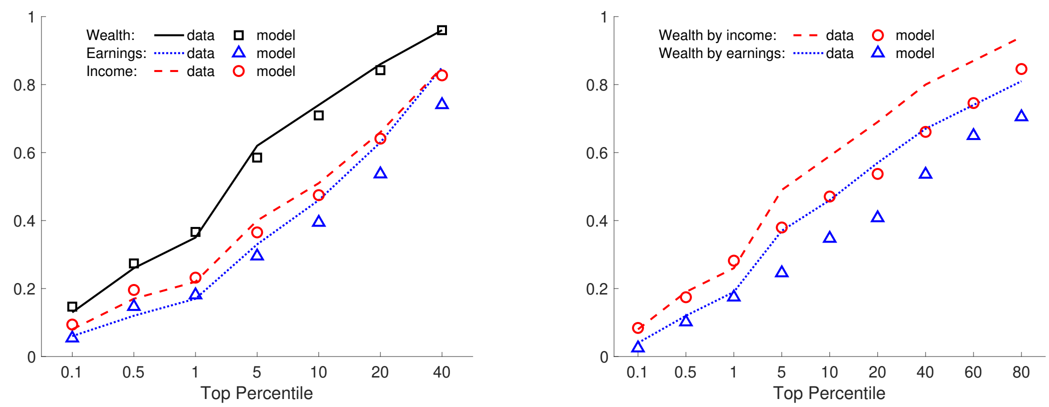
The model does not feature an explicit link between parents and their offspring, which requires a larger state space, and is computationally challenging. To capture the dynastic persistence of wealth, we assume that at age 50, the average age of bequest receipt in the data (Feiveson and Sabelhaus, 2018), agents randomly draw a bequest from a mixture of the bequest distributions of the deceased in the model, where the weights $\bar{\gamma}_z$ and $\bar{\gamma}_\kappa$ depend on the recipient's state. 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

[15] This 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 for the formal representation. See Guner et al. (2014), Heathcote et al. (2017) and Bakış et al. (2015) for evidence on the fit of this function.

Figure 3 – Distribution of Wealth, Income and Earnings

(a) Cross-sectional Distributions

(b) Wealth by Income and Earnings



Note.– Panel (a) shows the cumulative shares for the top percentile groups. Panel (b) shows share of net worth held by top income and earning groups. Data values come from SCF 2010 and 2016. Income includes capital gains.

a bequest from a high-productivity (high-return) parent. We calibrate $\bar{\gamma}_z$ and $\bar{\gamma}_\kappa$ to match the intergenerational correlation of 0.3 in wages (Solon, 1992) and of 0.37 in wealth (Charles and Hurst, 2003).[16]

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 earning and rate of return processes implied by the calibration. As an overidentification check, we also compare the model's implications for the evolution of earnings, income and net worth over the life-cycle.

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, at

[16]See Appendix C.5 for details.

Table 4 – Share of Income from Labor by Income Groups

	All	Top Percentiles				Quintiles				
	0-100	Top 0.1%	Top 1%	95-99	90-95	5th	4th	3rd	2nd	1st
Data	0.82	0.49	0.59	0.77	0.89	0.77	0.93	0.92	0.84	5.02
Model	0.80	0.47	0.61	0.85	0.81	0.78	0.86	0.86	0.77	0.02

Notes.– Data values come from the SCF (2001 - 2019).

least up to the top 0.1%. The overall Gini coefficient for net worth, which is not a calibration target, is 0.81 in the model – close to the data value of 0.84. Similarly, the concentration of income and earnings among top groups is in line with the data.

Panel (b) shows the shares of net worth held by different income and earning 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 95$^{\text{th}}$ and the 99$^{\text{th}}$ percentiles. This is due to the discreteness of our modeling of the productivity process.

Next, we compare the factor composition of income for different income groups in Table 4. Labor's share of income is 47% (61%) in the model for the top 0.1% (1%) of incomes, compared to a data value of 49% (59%). Labor's share for the wealthiest 1%, which is not targeted in the calibration, is 48%, close to the data value of 53%.

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 23 and 157 times as productive as the average worker, and they represent 0.76% and 0.03% of the population in equilibrium.[17] But earnings are a combination of productivity and hours worked. The earnings of the top 0.1 and 1 percent of earners are 54 and 18 times the average in the model, close to their empirical values of 60 and 17.

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

The distribution of earnings growth, which determines the earnings risk faced by top earners, is also reasonable. Guvenen et al. (2021) characterizes 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 12, and a skewness of -3, which are comparable to the data, even though they aren't explicitly targeted.[18] 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 62% in the model, identical to the estimate by Kopczuk et al. (2010).[19]

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 0.1%, 5.5% and 25.3%. But only 0.1% of households enjoy the top rate and 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, life-time rates of return across households is much smaller than in the cross-section: the average (unweighted) return is 2.3%, with a standard deviation of 2.75%.

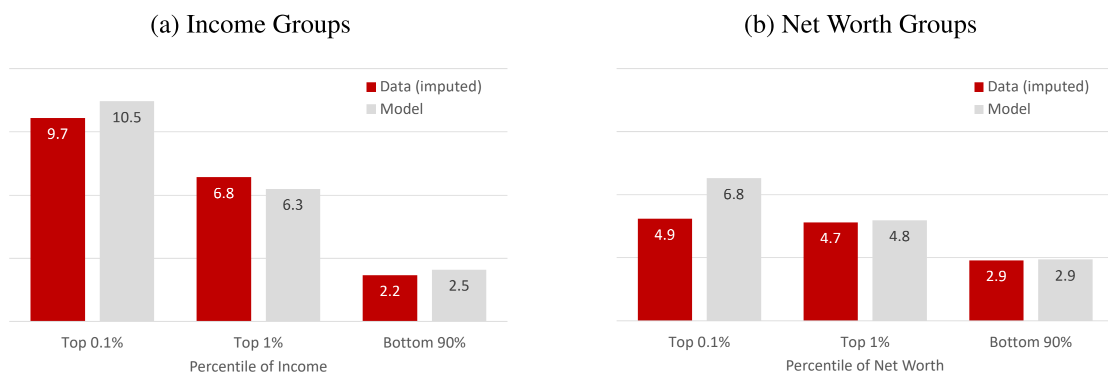
The calibration implies a positive correlation between the top earner status and the top investor status. Households with the highest labor productivity are 15 times more likely to enter the top return state than an ordinary household (Panel b of Table C.2). As a result, 1% of households in the top productivity 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). Model and data values are generally very close. Recall that the return for the top 0.1 and 1% income groups relative to the bottom 90% is a calibration target. The model thus fits the data values closely (panel a). Higher income groups have significantly higher returns. This reflects the higher propensity of top productivity households to enter the top return state as well as the effect of higher returns on income.

[18] The strong left skew is partly due to our assumptions on λ_{out}. It is significantly less pronounced when those leaving z_7 downwards all enter z_6. Yet, this change hardly affects our quantitative findings below.

[19] These studies are based on individual earning records from the Social Security Administration. To our knowledge, corresponding statistics are not available at the household level.

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.

The model also closely replicates returns for different wealth groups (panel b), which were not targeted in the calibration. Higher wealth groups have modestly higher returns on average. This scale dependence is not hardwired in the model—it emerges endogenously as households with higher returns are more likely to be wealthy. The main difference in wealth accumulation across wealth groups therefore comes from differences not in asset returns, but in saving rates, in line with the data. The saving rate out of income among the wealthiest 1% is 41% compared to the 21% for the aggregate economy. These findings are consistent with Saez and Zucman (2016), who report small differences in rates of returns but large differences in saving rates across wealth groups in the data.

6.4 Implications for life-cycle dynamics

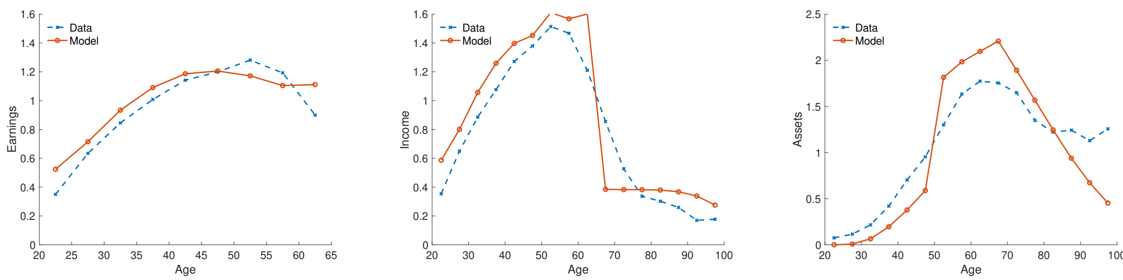
Next, we compare the model's implications for the evolution of income, earnings and wealth over the life-cycle with data. Since these are not targeted explicitly (with the exception of the age profile of wages), we view this comparison as a test of the model's ability to accurately capture the savings and labor supply behavior among households.

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 overshoots the data for 50 year olds, when agents receive all their bequests, and undershoots the data for 85 and over.[20]

[20]Excess dissaving near the end is a known characteristic of life-cycle models (see e.g. De Nardi et al.

Figure 5 – Earnings, Income and Wealth over the Life-Cycle

(a) Earnings (b) Income (c) Net Worth



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.

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 profiles of wages, which we target, and wealth, which we do not. Similarly, income rises until retirement, albeit at a faster rate reflecting both higher earnings and higher capital income, and is flat after retirement.[21]

Figure 6 compares the evolution of earnings and wealth dispersion with the data. The rise in earning 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.

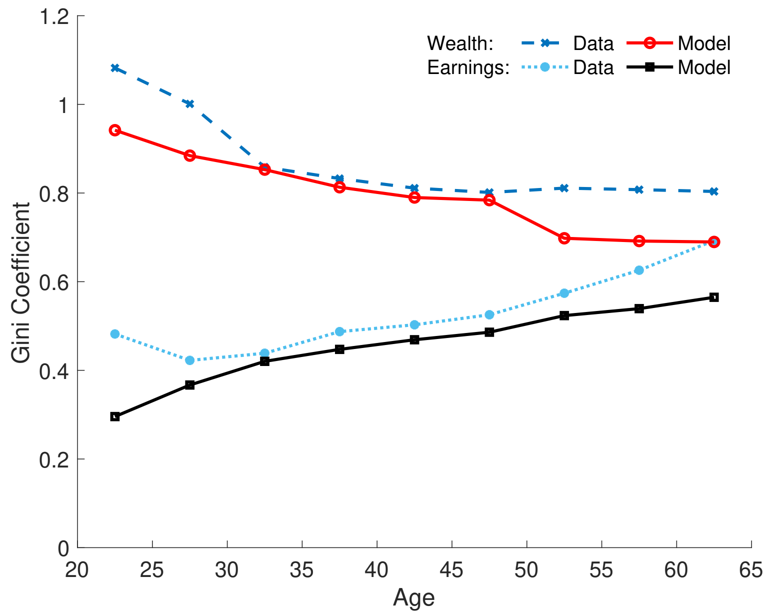
The Gini coefficient for wealth is initially high, because most young households have little assets and weak saving motives in anticipation of earnings growth. With age, asset accumulation becomes more prevalent as earnings grow and retirement approaches. This reduces the Gini coefficient early on in the life-cycle. About 20 years later, 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

(2009)). It does not affect aggregate bequests, since most households die before reaching these ages.

[21]The model also generates plausible age profiles across the distributions. For instance, the average age in the top 1% of wealth (income) is 62 years (56) in the model, compared to 60 (55) in the data.

Figure 6 – Earnings and wealth inequality over the Life-Cycle



both in the short run and over the life-cycle. The factor composition of income is realistic, 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. Each of the remaining rows takes away a critical model component and reports the counterfactual moments.

First, we investigate the effects of bequest inequality by simulating an economy where bequests are distributed equally. In this scenario, the Gini coefficient for wealth drops sub-

Table 5 – Determinants of Wealth Concentration: A Decomposition Analysis

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
benchmark	0.81	0.15	0.37	0.054	0.18
Counterfactual economies with …					
…(1) equal bequests	0.71	0.09	0.28	0.054	0.18
…(2) no top earners	0.72	0.10	0.18	0.005	0.04
…(3) common returns	0.75	0.08	0.28	0.052	0.18

Note.– Results from model simulations. Economy (2) sets the extraordinary productivity levels to that of the highest "regular" earnings category ($z_8 = z_7 = z_6$). Economy (3) sets $r\kappa$ to its value-weighted average in the benchmark economy.

stantially, from 0.81 to 0.71, roughly the difference between Canada and the US. Top wealth shares fall by 25% to 40%. Overall, bequest inequality has a significant impact on the wealth distribution, as it perpetuates wealth dispersion across generations.[22]

Next, we remove superearners from the benchmark economy by equating the productivity at the two extraordinary states to the highest "ordinary" level: $z_8 = z_7 = z_6$. This preserves the wage distribution among the remaining states.[23] 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 0.5% 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 37% to 18%, and that of the wealthiest 0.1% from 15% to 10%.[24] Because there still is substantial earnings dispersion outside of the top groups, the overall drop in wealth dispersion, while sizable, is less extreme—the Gini coefficient drops from 0.81 to 0.72.

Finally, we equalize rates of return by setting $r\kappa_i$ to its value-weighted average in the benchmark economy for all households. Doing so reduces the Gini coefficient for wealth from 0.81 to 0.75 and the top 1% wealth share from 37% to 28%. The top 0.1% share falls strongly, from 15% to 8%. These are significant reductions in top wealth shares.[25]

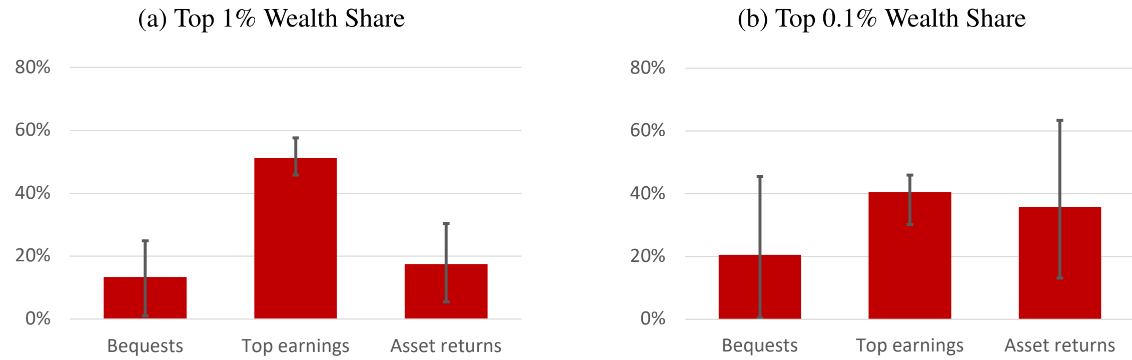
[22]In the Appendix, we investigate the role of non-homotheticity and intergenerational links. In both cases, the effects are qualitatively similar to equal distribution of bequests, but quantitatively smaller (Table D.2).

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

[24]Most of the decline in the top 0.1% wealth share is due to the reduction in z_8, while most of that in the top 1% share is due to the change in z_7. (See Appendix Table D.2.)

[25]Most of the reduction in top wealth shares stems from eliminating the top return, as setting $\kappa_{\text{top}} = \kappa_H$

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.

Eliminating the different components individually may mask potential interactions between them. 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 to wealth concentration.[26] The bars represent the average of four marginal effects expressed as a fraction of the benchmark value. Whiskers show the smallest and the largest marginal effects.

The contribution of top earners to wealth concentration is large and stable across permutations. On average, removing top earners reduces the top 1% wealth share by about a half and the top 0.1% share by around 40%.

The contribution of bequests and asset returns to top wealth shares, in contrast, varies much more strongly across permutations. On average, equalizing bequests reduces top wealth shares by about 20%. The average effect of return heterogeneity on the top 1% wealth share is similar, whereas the average effect on the top 0.1% is twice as large, at almost 40%, with a wide range, from just about 10% to over 60%.

Further examination reveals that equalizing bequests has a particularly large effect on top wealth shares in economies with heterogeneous returns. With common returns, bequest inequality hardly affects wealth concentration. Conversely, return heterogeneity contributes

produces a smaller change in the Gini but similar changes in top shares. (See Appendix Table D.2.)

[26]The simulation results for all permutations are reported in Table D.1 in the Appendix.

more to wealth inequality when bequests are unequal. This pattern indicates a complementarity between return heterogeneity and bequest inequality in generating wealth inequality to which we return below. Bequests do not add much to wealth concentration on their own, but they amplify the other channels, in particular return heterogeneity, by perpetuating within-generation wealth inequality across generations in a dynasty.

In contrast, the effect of eliminating superearners is similar across permutations.

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 pitfalls from ignoring either channel.

First, we eliminate superearners by setting $z_8 = z_7 = z_6$, and raise the top return to $\kappa_{top} = 0.27$ to match the empirical value for the top 0.1% wealth share. Second, we set all κ to its asset-weighted mean in the benchmark and raise the highest productivity level (z_8) to match the top 0.1% wealth share. By construction, both models match the top 0.1% wealth concentration in the data. But they deviate from the data in other dimensions.

The economy without superearners features too low concentration of earnings 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 0.5%, respectively, much below their empirical counterparts of 17% and 6%. Among top income groups, the implied labor share of income is 0.31, compared to 0.59 in the data. Top wealth groups rely almost exclusively on capital income, with a labor share of income of 7%, 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.[27]

[27] Equation (1) gives the labor share of the wealthiest 1% as a function of their relative assets, $k_{1pct/0} = 33.6$

In contrast, an economy with homogeneous returns features an excessively high labor income share among high income earners, at 79% (87%) 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 benchmark. This world is reminiscent of the economy in Castañeda et al. (2003).

Taken together, these exercises illustrate how the labor share of top income groups along with the empirical earnings concentration are 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.

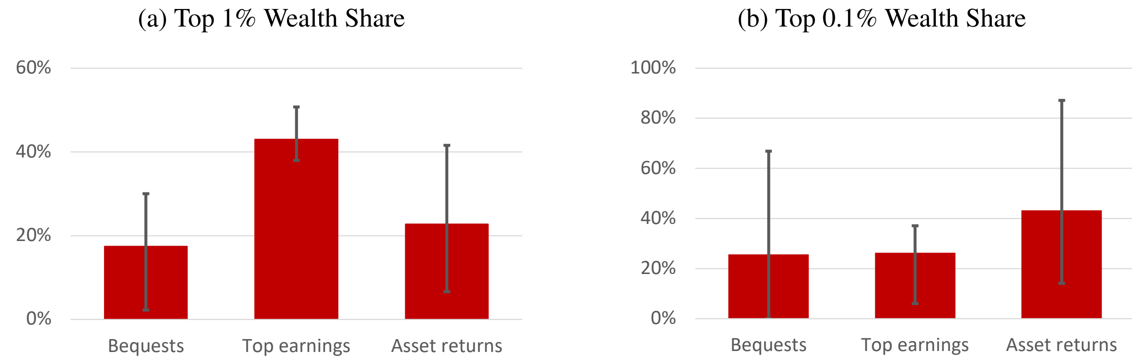
The two issues discussed in Section 3, in particular, relate to the factor composition of business income and to accrued capital gains, which do not show in income. Ascertaining the labor share of income among entrepreneurs is inherently difficult. Here, we consider the extreme alternative of allocating 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.[28]

In what follows, we compute all relevant data moments under this assumption and fully 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%, much lower than our preferred measure of 59%. 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 4.5 and 3.1 for the

(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.

[28] Larrimore 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.

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.

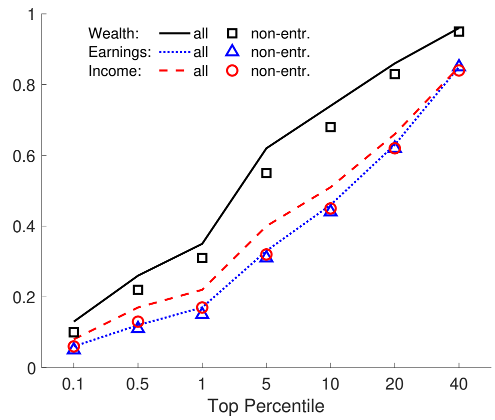
top 0.1% and 1% of the income distribution to 3.6 and 2.5.

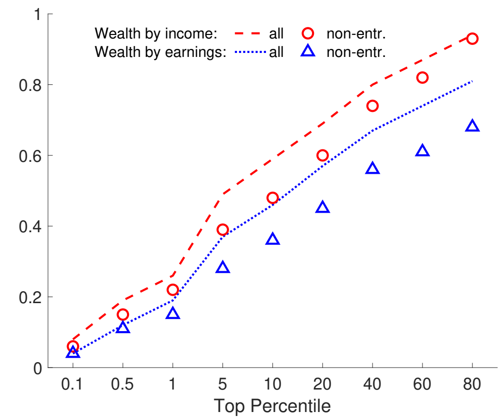
Repeating the decomposition analysis above yields a lower contribution of earnings heterogeneity to wealth concentration and a higher contribution of return heterogeneity (Figure 8). On average, eliminating top earners now reduces the top 1% wealth share by 43% instead of 51%, and the top 0.1% wealth share by 26 instead of 40%. The role of asset returns increases from 17% to 23% for the top 1%, and from 36% to 43% for the top 0.1%. The importance of bequests increases on average by 4 percentage points. Overall, superearners remain the main driver of the top 1% wealth share, even at its lower bound, while return heterogeneity becomes even more important for the wealthiest 0.1%.

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 other households with similar characteristics, then we would expect different roles for

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





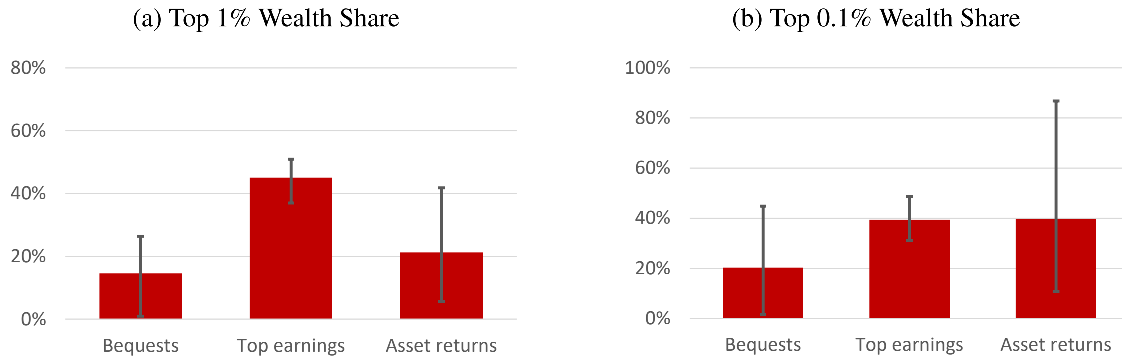
Note.– The left panel shows the marginal distributions. The right panel shows the share of net worth held by top income and earning groups. Source: Author's calculations from SCF 2001 to 2019.

labor and capital in wealth concentration in this alternative calibration.

To begin, we drop all entrepreneurial households from our data, and compare the distributions of earnings, income and wealth with those in the benchmark economy (Figure 9a). Excluding entrepreneurs lowers the concentration of net worth and earnings, but not by much. Among non-entrepreneurial households, the wealthiest 1% holds 31% of their combined wealth, compared to 35% among all households in the benchmark. This is consistent with disproportionate prevalence of entrepreneurs among the wealthiest households. It also suggests, however, that there is considerable wealth dispersion within the rest of the population. Earnings concentration falls slightly: the top 1% earnings share is 17% in the benchmark and 15% when entrepreneurs are excluded. The correlation between earnings and wealth is slightly weaker as well (Figure 9b). For instance, the wealth share of the top 1% earners is 15% for non-entrepreneurs versus 19% for the population. Since entrepreneurial households rely more heavily on capital income, labor's income share is higher when they are excluded: 74% (70%) among the top 1% (0.1%) compared to 59% (49%) in the benchmark. Because labor shares are similar among non-entrepreneurial households, the implied dispersion in rates of return (see Section 3.4) is also lower. For the top 0.1% (1%) non-entrepreneurial households by income, relative rate of returns are 3.6 (2.5) times those of the bottom 90%, compared to 4.4 (3.1) in the benchmark.

Not surprisingly, these figures show that earnings, income and wealth of entrepreneurs

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.

are more concentrated, that top entrepreneurs derive less of their income from labor, and that they earn higher returns. 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 high concentration of earnings, income and wealth, as well as differences in rates of return.[29]

To quantify the marginal impact of entrepreneurs on the wealth distribution, we recalibrate four parameters of the model to fit the top 0.1% and top 1% earnings shares as well as the top 0.1% and 1% relative rates of return observed in the data among non-entrepreneur households. We also set π_{in} to its level for states z_1 to z_6 for all z. Importantly, we do not target any moments related to wealth concentration.

The resulting wealth distribution is less concentrated, with a top 1% share of 0.33 versus 0.37 in the benchmark. The Gini coeficient falls to 0.79 from 0.81. These results suggest that entrepreneurs are indeed different from other households, but also that the difference may not be large enough to change our results. Indeed, repeating the decomposition analysis in this world without entrepreneurs, we find that earnings is the primary factor behind wealth concentration, with the exception of the wealthiest 0.1% who benefit similarly from high earnings and and high returns (Figure 10). Comparing Figures 7 and 10 reveals that our findings regarding the relative contribution of factors changed little, indicating that not much generality is lost by our treatment of entrepreneurs.

[29]It 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 heterogeneity is the primary driver of wealth concentration in the US. Heterogeneous capital returns play an equally critical role, but mostly for the wealthiest of households. 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).[30] It is important to note, however, that these theoretical results pertain to specific settings which 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 life 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 tail fatter 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).

The same features also keep the quantitative relevance of rate of return heterogeneity in check. To see the importance of initial wealth on wealth concentration, imagine a scenario where agents received all their inheritances at the age of 20, instead of 50 as in our benchmark. This would allow rate of return differences to raise wealth concentration over a longer horizon. The top 1% wealth share, we find, would increase to 40% from 37%.

[30] Stachurski 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.

Eliminating return heterogeneity would then lower that by a third, not by a quarter as in our benchmark.[31] Since young households have little wealth in reality, this mechanism has a more modest effect in the benchmark analysis.

Life expectancy also matters. A high earning household (at thrice the average wage, say) would join the top 1% of the wealth distribution only at age 45 and the top 0.1% at age 55 even if they permanently earned the highest return on assets. Rate of return differences are known to take a long time to manifest their impact on the wealth distribution (Gabaix et al. (2016)), and human life is simply too short for that to play out.

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.[32] This arises because the wealthiest 1% have 27 times 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.[33]

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.[34] If we re-calibrate

[31] Conversely, eliminating top earners in this imaginary world would reduce the top 1% wealth share by 39%, compared to 50% in the benchmark analysis.

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

[33] This number is 44% on average over the SCF waves 2001 to 2019, and 47% in our benchmark economy.

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

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 6% from 17%, we too understate the wealth concentration, producing a Gini coefficient of 0.73 and a top 1% share of 19% 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.2 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 (Karahan et al., 2019), and production complementarities or changes in the degree of assortative matching both between workers and firms and among workers across firms (Geerolf, 2016; Song et al., 2019).

Another promising avenue is entrepreneurial activity, since earnings concentration is partly driven by the 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 capital (or 'sweat equity') is transferable upon sale of a business. Similarly, Smith et al. (2019) attribute three quarters of pass-through business profits to 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.

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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:

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

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:

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

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 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.

[A1]The public use data files are available for download at https://www.federalreserve.gov/econres/scf-previous-surveys.htm.

Second, we impute wage income 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 the 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. 3% of all the households in our imputation sample 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 who 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 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	0.50	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: Author's calculations from SCF 2001 – 2019

Table B.1 shows the values for 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 salary from their business, no imputation is made, and we report business income separately. These figures are comparable to the top

[A4]As common in the literature, we use the demographic measures, educational attainment and occupation for the head of the household as details are not available for each member of the household who actively participates in the business. Omitting those variables related to the quality of the labor input altogether and including only total number of hours worked results in an estimate 0.32 (0.01) instead.

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

	Income Percentile Category				
without capital gains	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
	Income Percentile Category				
with capital gains	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 constitute 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

[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 is based on tax units whereas the SCF data is based on primary economic units, which consists of the core members of the household. In most cases, this includes the respondent, their spouse, if any, and their dependent children.

is 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 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 (Benabou, 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 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.2 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

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

where $\tilde{e}(z)$ are average earnings of working age agents of productivity z in the model's stationary equilibrium. The formula reported by 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.3 Labor Productivity Process

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
$z_2 = 1.97$	0.060	0.878	0.060	0	0	0	0.002	0
$z_3 = 3.89$	0.004	0.119	0.874	0	0	0	0.002	0
$z_4 = 3.24$	0	0	0	0.874	0.119	0.004	0.002	0
$z_5 = 6.39$	0	0	0	0.060	0.878	0.060	0.002	0
$z_6 = 12.61$	0	0	0	0.004	0.119	0.874	0.002	0
$z_7 = 137.36$	0.021	0.021	0.021	0.021	0.021	0.021	0.850	0.021
$z_8 = 1349.46$	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	0.097	0.303	0.097	0.097	0.303	0.097	0.0076	0.0003

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.

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 is different from the invariant distribution. The population shares for the working age population are reported in the last row of the

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 (%)	0.1	5.5	25.3

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}	4.9×10^{-4}	3.7×10^{-3}

Note.– The top panel shows the transition probabilities in the benchmark economy from the rate of return in Column 1 to rates of returns 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. Retired agents have zero labor productivity.

C.4 Stochastic Process for Rate of Returns

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

C.5 Modeling of Bequests

The model does not feature an explicit link between parents and their offspring, which requires a larger state space, and is computationally challenging. To capture the dynastic persistence of wealth, we assume that at age 50, the average age of bequest receipt in the data (Feiveson and Sabelhaus, 2018), agents randomly draw a bequest from a mixture of the bequest distributions of the deceased in the model. Concretely, we assume that a recipient with permanent productivity component i' and saving return j' draws from the distribution of bequests left by deceased agents with permanent productivity component i and return j ($i, j, i', j' = L, H$) with probability $\gamma(i', j'; i, j)$. For this purpose, we treat the top productivity states z_7, z_8 like f_H, and the top return state κ_{top} like κ_H. To limit the number of

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

Parameter	Description	Value	Source
		Demographics	
J	Maximum life span	16	corresponds to age 100
J_R	Mandatory retirement age	10	corresponds to age 65
s_0, s_1, s_2	Survival probability by age	-5.49, 0.15, 0.016	Halliday et al. (2019)
		Preferences	
σ_c	Risk aversion	1.5	
σ_l	Inverse Frisch elasticity	1.22	Blundell et al. (2016)
		Technology	
δ	Depreciation (annual)	0.045	
		Labor productivity	
		See Sections 5.3 and C.3	
		Taxes and transfers	
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

parameters, we model $\gamma(i', j'; i, j)$ as $\gamma_z(i, i')\gamma_\kappa(j, j')\bar{\Gamma}(i, j)/\tilde{\Gamma}(i', j')$, where $\gamma_z(i, i')$ equals the parameter $\bar{\gamma}_z \in [0, 1]$ if $i = i'$ and $1 - \bar{\gamma}_z$ otherwise, and analogous for $\gamma_\kappa(j, j')$. $\bar{\Gamma}(i, j)$ denotes the fraction of deaths with states (i, j), and $\tilde{\Gamma}(i', j') = \sum_{i,j} \gamma(i', j'; i, j)$ ensures that the probabilities sum to one.

This formulation 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. We calibrate $\bar{\gamma}_z$ and $\bar{\gamma}_\kappa$ to match the intergenerational correlation of 0.3 in wages (Solon, 1992) and of 0.37 in wealth (Charles and Hurst, 2003).

C.6 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.4 – Calibration of the Model: Jointly Calibrated Parameters

Parameter	Description	Value	Parameter	Description	Value
β	Annual Discount rate	0.989	θ	Labor disutility	6.0
α	Capital elasticity	0.27			
z_7, z_8	Top productivity states	Table C.1	$\lambda_{in}, \lambda_{ll}, \lambda_{lh}, \lambda_{hh}$	Transition rates	Table C.1
$\kappa_L, \kappa_H, \kappa_{top}$	Rates of return	Table C.2	$\pi_{ll}, \pi_{hh}, \pi_{in}, \pi_{top,top}$	Transition rates	Table C.2
τ_l	Tax progressivity	0.17	d_c	Corporate asset threshold	2.21
ξ	Pension / Earnings	0.62	G/Y	Expenditures / GDP	11.6%
ϕ_1, ϕ_2	Bequest utility	-0.42, 0.19	$\bar{\gamma}_z, \bar{\gamma}_\kappa$	Bequest correlations	0.65, 0.9

Table C.5 – Summary of Target Moments

Moment	Source	Data Value	Model Fit	Moment	Source	Data Value	Model Fit
Mean hours worked		0.35	0.35	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	Kopczuk et al. (2010)	0.62	0.62
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	0.38
Bequest/Wealth	Guvenen et al. (2019)	$\sim 1\%$	1.7%	Top 2% bequest dist.	Feiveson and Sabelhaus (2018)	40%	47%
Difference between average income tax rate for top 1% and 99%	Piketty and Saez (2007)	12.4%	12.5%	Corporate income tax revenue/GDP	NIPA	2.5%	2.2%
Overall labor income share	SCF 2010–2019	0.82	0.80	Top 0.1% labor income share	SCF 2010–2019	0.49	0.47
Top 1% labor income share	SCF 2010–2019	0.59	0.61	P95-99 labor income share	SCF 2010–2019	0.77	0.84
Intergenerational wealth persistence at 4th quintile	Charles and Hurst (2003)	0.26	0.22	Intergenerational wealth persistence at 5th quintile	Charles and Hurst (2003)	0.36	0.32
Mean return top 0.1% / bottom 90%	SCF 2001–2019	4.5	4.3	Mean return top 1% / bottom 90%	SCF 2001–2019	3.2	3.6

D Supplementary Tables and Results

Table D.1 shows the details of the counterfactual economies used to calculate the marginal contributions of superearners, bequests and asset returns depicted in Figure 7. The benchmark economy (0) is reported in the first row. Each counterfactual economy removes the factors of wealth concentration in different combinations. Economies 1, 2 and 3 are repeated from Table 5 in the main text. For each factor, four different marginal effects were computed. The marginal contribution of rate of return heterogeneity to top 1% wealth share, for instance, were computed as follows: by the difference between the benchmark economy (0) and the counterfactual economy (3) where only the rate of return differences are eliminated, which gives $0.09 = 0.37 - 0.28$; by the difference between economy (2) where superearners are absent and economy (2)+(3) where both superearners are absent and asset returns are common, which gives, $0.11 = 0.18 - 0.07$; by the difference between economy (1) with equal bequests and economy (1)+(3) with equal bequests and common asset returns, which gives $0.03 = 0.28 - 0.25$; and, finally, by the difference between economy (1)+(2) with equal bequests and without superearners and economy (1)+(2)+(3) where all three factors are inactive, which gives $0.04 = 0.11 - 0.07$. The whiskers in Figure 7 represent the minimum and the maximum values of the four different marginal effects, namely 0.03 and 0.11, relative the benchmark top 1% wealth share of 0.37. The height of the bar represents the average marginal effect across the four marginal effects relative to the benchmark value. The marginal effects for other factors are calculated in a similar fashion.

Table D.2 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 (2a), 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 (3a), 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.

Table D.1 – Determinants of Wealth Concentration: A Decomposition Analysis

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
... (0) benchmark	0.81	0.15	0.37	0.05	0.18
counterfactual economies with . . .					
(a) remove individual channels					
. . . (1) equal bequests	0.71	0.09	0.28	0.05	0.18
. . . (2) no top earners	0.72	0.10	0.18	0.005	0.04
. . . (3) common returns	0.75	0.08	0.28	0.05	0.18
(b) remove combinations of channels					
. . . (1)+(2) equal bequests & no top earners	0.64	0.04	0.11	0.005	0.04
. . . (1)+(3) equal bequests & common returns	0.69	0.08	0.25	0.05	0.18
. . . (2)+(3) no top earners & common returns	0.63	0.01	0.07	0.005	0.04
. . . (1)+(2)+(3) all three channels removed	0.60	0.01	0.07	0.008	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 represents different combinations of these scenarios.

Table D.2 – Determinants of Wealth Concentration: Additional Decomposition Results

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
... (0) benchmark	0.81	0.15	0.37	0.05	0.18
counterfactual economies with ...					
... (1a) homothetic bequests	0.78	0.14	0.35	0.06	0.18
... (1b) uncorrelated bequests	0.77	0.13	0.34	0.05	0.18
... (2a) $z_8 = z_7$	0.79	0.11	0.33	0.03	0.16
... (3a) $\kappa_{\text{top}} = \kappa_H$	0.77	0.08	0.29	0.05	0.18

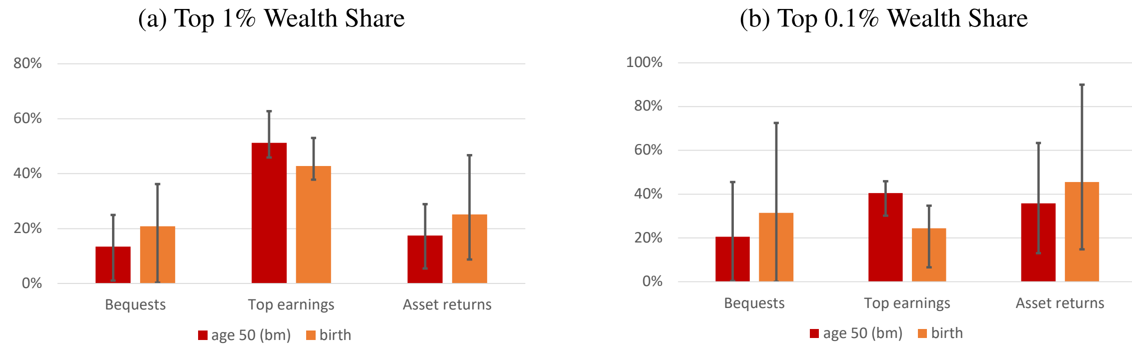
Note.– Results from model simulations. In counterfactual economy (1a), we set ϕ_2 to zero, making the bequest motive homothetic. In (1b), we remove the correlation of bequests with parental wealth by setting both $\bar{\gamma}_z$ and $\bar{\gamma}_\kappa$ to 0.5, so that all bequest recipients draw their bequest from the same distribution. In (2a), 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 (3a), we set the top excess return, κ_{top}, equal to the higher regular excess return, κ_H.

In the benchmark economy, agents receive their bequests when they are 50 years old, the median age of receipt in the data. If the households were to receive all their bequests earlier, then the impact of return on heterogeneity on wealth concentration would be stronger. Figure D.1 compares the marginal contribution of each factor in the benchmark economy with a hypothetical economy where all bequests are received at age 20, when agents enter the labor market. Once again, 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.

D.1 Sensitivity to Labor Share Estimates

In Section 8.2, we recalibrated 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 re-calibrate the entire model. Here, we report the main changes in parameters. Most importantly, the lower top labor income shares also imply a lower aggregate labor income share, and therefore a

Figure D.1 – Factors of Wealth Concentration, by age of bequest receipt



Note.– Figure shows the marginal contribution of each factor to the concentration of net worth relative to the benchmark economy, by age of bequest receipt. In the benchmark, bequests are received at age 50. In the alternative scenario, at labor market entry ("birth"). 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.

higher value for α, at 0.32. Lower top LIS also imply lower top productivity: z_8 is 30% lower than in the benchmark, and z_7 10% lower. In addition, the probability of leaving z_8 (z_7) is 40% (20%) higher. Generating the same wealth concentration with lower top earnings requires higher returns: κ_H (κ_{top}) is 2.2 (1.2) percentage points larger. Intergenerational persistence of the high return state is 0.92 instead of 0.9. Finally, the probability that top earners enter the top return state drops from 2 and 15 times that of ordinary earners to 0.5 and 0.7 times, respectively. To keep the same capital-output ratio as the benchmark economy also requires an adjustment in β, from from 0.989 (annual) to 0.980.

Table D.3 shows the main decomposition results for this economy. All results are summarized in Figure 8 in the main text.

D.2 An Economy with Low Earnings Concentration

Figure D.2 and Table D.4 shows decomposition results for an economy with a counterfactually low earnings inequality, as discussed in Section 9 in the main text. In particular, we re-calibrate 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 6% (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 0.73 and a top 1% wealth share of 19%. This Gini coefficient is

Table D.3 – Determinants of Wealth Concentration: Excluding Imputed Wages for Entrepreneurs

	wealth Gini	top wealth shares		top earnings shares	
		0.1%	1%	0.1%	1%
benchmark	0.81	0.13	0.35	0.04	0.16
Counterfactual economies with …					
…(1) equal bequests	0.70	0.08	0.25	0.05	0.16
…(2) no top earners	0.75	0.11	0.22	0.004	0.04
…(3) common returns	0.73	0.06	0.25	0.04	0.16

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.

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 by 40 to 60%, 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 of about 10%.

Table D.4 – 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	0.81	0.15	0.37	0.054	0.18
Alternative economy with earnings Gini = 0.41					
	0.73	0.10	0.19	0.01	0.06
Counterfactual economies with low earnigns inequality and . . .					
. . . (1) equal bequests	0.64	0.04	0.12	0.01	0.06
. . . (2) no top earners	0.72	0.10	0.18	0.01	0.04
. . . (3) common returns	0.65	0.01	0.09	0.01	0.06

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 earnigns of 0.41. Counterfactual economies are generated as in Table 5 above.

Figure D.2 – Factors of Wealth Concentration – alternative economy with low earnings inequality

(a) Top 1% Wealth Share

(b) Top 0.1% Wealth Share

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.