Accounting for the determinants of wealth concentration in the US

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Abstract

What are the fundamental determinants of the high level of wealth concentration in the US? The recent literature has put forward high concentration of labor income, capital income risk and bequests as potential reasons. We use data on the joint distribution of earnings, capital income and wealth to identify the quantitative importance of each driving force, and find that labor income concentration is the most important source of wealth dispersion for almost the entire distribution. Some heterogeneity in asset returns is required to match the factor composition of top incomes. It mostly contributes to the fat right tail of the wealth distribution, and to the share of the wealthiest 0.01% of households. These findings reflect the high correlation between earnings and wealth in the data, as well as the fact that earnings account for a large part of income even at the top of the income distribution.

J.E.L. Codes: D31, H24

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1 Introduction

Wealth holdings in the U.S. are highly concentrated. Recent statistics show that the wealthiest 20% of the population holds 87% all assets, with the wealthiest 1% alone holding 34% of total assets (Kuhn & Ríos-Rull 2016). The recent literature has emphasized a set of competing factors that can lead to such a high concentration of wealth. A first strand highlights the role of labor income heterogeneity and earnings risk, which lead to high saving rates among high earnings groups (Castañeda et al. 2003, Kindermann & Krueger 2014, Kaymak & Poschke 2016). A second strand highlights the role of capital income heterogeneity, where some households have access to investment vehicles (or businesses) with persistently higher rates of return (Quadrini 2000, Cagetti & De Nardi 2006, Benhabib et al. 2015). A third factor consists in the dynastic accumulation of wealth through bequests (see, for instance, De Nardi (2004)).[1]

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[1]See De Nardi & Fella (2017) for a recent review of the macro literature on wealth inequality.

These approaches differ in their depiction of who the wealthiest are and how they became wealthy. As a result, they can reach quite different conclusions in their assessments of the effects of economic policy. For instance, using a model of labor income uncertainty, Kindermann & Krueger (2014) prescribes an optimal marginal tax rate as high as 90% for top income groups, whereas Brüggemann (2017) calls for a tax rate of 52.5% based on a model of entrepreneurship. Similarly, Hubmer et al. (2016) attribute much of the rise in wealth concentration over the last 50 years to top income tax cuts, whereas, in earlier work, Kaymak & Poschke (2016) find the rise in the dispersion of wage income to be the major factor behind the recent trends in wealth inequality. Guvenen, Kambourov, Kuruscu, Ocampo & Chen (2015) argue that wealth taxes may bring efficiency gains relative to capital income taxation in models with rate of return heterogeneity. Clearly, answering the questions addressed by these papers requires a better understanding of the relative quantitative importance of the factors that shape the U.S. wealth distribution and lead to its heavy concentration at the top.

Regrettably, a direct empirical assessment of how important labor and capital income are for generating large fortunes in the U.S. is infeasible due to the lack of a long panel data on earnings, asset holdings and the rates of return on those assets at the household level. Nonetheless, data is available on the cross-sectional distributions of earnings, income and wealth as well as the sources of income for different income groups in any given year. In this paper, we combine this information with an overlapping generations model that features labor income risk, rate of return heterogeneity as well as bequest motives to assess the relevance of the different modeling approaches to wealth concentration. In particular, we use the joint distribution of income and wealth as well as the factor composition of income for top income groups to identify the quantitative importance of earnings concentration and rate of return heterogeneity for the wealth distribution in the U.S.. This crucial identifying information has not previously been used in the literature on the wealth distribution, which has focused exclusively on marginal distributions of earnings and wealth.

The results show that a model with all three mechanisms generates realistic marginal and joint distributions of earnings, income and wealth. It also generates realistic life-cycle profiles of average earnings, income, and wealth, as well as their cross-sectional dispersion by age. However, our results also reveal that models that rely only on differences in the rate of return on savings to generate a skewed wealth distribution predict a counterfactually high role for capital income at the top of the income distribution. Relative to the data, the implied correlation between income and wealth is too high, since wealth is the primary source of high incomes in this case, and the correlation between earnings and wealth is too low. On the other hand, models that rely on labor income risk alone exaggerate the correlation between earnings and wealth, and require an earnings concentration at the top that is counterfactually high.

Preliminary results from a version of the model that is estimated using the joint empirical distribution of earnings, income and wealth indicate that some rate of return heterogeneity is required to match the income composition of top income households. As a consequence, rate of return heterogeneity has some impact on wealth concentration, in particular for a small group of households who are at the extreme right tail of the income and wealth distributions (top 0.1 or 0.01 percent). The dominant factor driving wealth concentration for most of the distribution, however, consists in the concentration of earnings, combined with strong saving incentives for top earners. The second most important factor is the bequest motive. If all bequests were accidental, the model predicts 20% lower top wealth shares.

In the next section, we give a brief overview of the related literature. Then, we summarize the empirical distributions of earnings, income and wealth in the U.S., as well as the factor composition of income for different income groups. In Section 4, we present the model. Section 5 describes the calibration procedure and presents the results. Section 6 discusses the relative roles of rate of return heterogeneity, labor income risk and bequests in determining the observed distribution of wealth in the U.S.. Section 7 concludes.

2 Recent Developments in Macroeconomics of Wealth Distribution

The foundations of modern macroeconomic analysis of the wealth distribution are laid out in early work by Huggett (1993) and Aiyagari (1994), which eventually led to the "standard" incomplete markets model (Heathcote et al. 2009). In this setting, dispersion in asset holdings emerges from households' motives to accumulate assets in order to insure themselves against fluctuations in their earnings. The early iterations of these models focused on the implications of household heterogeneity for aggregate macroeconomic outcomes, such as the role of precautionary savings for total capital accumulation or the business cycles. It was nonetheless noted that the observed differences in earnings and the income risk as measured in household income surveys (e.g. PSID), were not large enough to generate a highly skewed distribution of wealth. Subsequently, a separate literature emerged aiming to enhance the model for applications to questions related to wealth inequality. The macro literature on wealth distribution is vast, with several applications to various economic questions. In our discussion of the literature below, we focus on main modeling extensions and their implications for a subset of applications as an example.

The main shortcoming in the original model was that the wealthy households cared little about the earnings income risk, and, therefore, limited their savings once their wealth was sufficiently high to shield consumption against future drops in earnings. The first modeling extensions that helped maintain continuing wealth accumulation, and, thereby, generate a skewed wealth accumulation involved introducing differences in savings rates or rates of return on assets. This was achieved by explicitly modeling heterogeneity in preferences for savings (Krusell & Smith 1998), in rates of return on assets (Quadrini 2000), entrepreneurs, who have both different motives for saving and different rates of return on their businesses (Cagetti & De Nardi 2006), as well as bequest motives that are increasing in wealth (De Nardi 2004). More recently, Benhabib et al. (2011) show analytically that idiosyncratic capital income risk is a necessary ingredient for generating a Pareto tailed wealth distribution with a realistic tail index. Benhabib et al. (2015) and Cao & 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 income on capital. High wealth concentration emerges because wealthy households enjoy higher rates of return on their assets and have higher saving rates out of income.

A second strand of the literature focused on better measurement of earnings risk. Panel surveys on household 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) was 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. Recent work further developed this approach, using the recent progress in measurement of top earnings levels based on administrative data to discipline the extent of earnings dispersion and risk input in the model (Kindermann & Krueger 2014, Kaymak & Poschke 2016). The economic mechanism here is that households who temporarily have very high earnings anticipate lower future earnings, 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, labor income risk, and the associated saving behavior.

Both approaches substantially improved the ability of the standard incomplete markets model to generate a realistic wealth distribution for the U.S., offering macroeconomists with several modeling options. The existing literature has operated with either a model with capital income risk or one with high earnings dispersion. The relative roles of earnings risk and capital income risk in generating the observed wealth concentration is nevertheless not well understood, in part due to lack of data on the dispersion of rates of return on assets at the household level for the U.S..[2] This paper combines the two approaches, and uses information on the joint distributions of earnings, capital income and assets to identify the relevance of different modeling approaches to wealth concentration.

3 Distributions of Income and Wealth in the US

In this section we summarize the empirical facts on the joint distributions of earnings, income and wealth, and discuss the data moments that are crucial for identifying the role of capital income risk vis-à-vis earnings risk for top income and wealth groups. The primary source of data is the Survey of Consumer Finances (SCF), a triennial cross-sectional survey of U.S. families on their assets, income, and demographic characteristics. We also compare our results with the statistics inferred from other sources in the literature based on administrative tax records.

For the analysis, we use the 2010 and 2016 surveys and exclude the 2013 survey, which reports income from the 2012 calendar year. In 2012, there is an unusual increase in realized capital gains stemming from an anticipated increase in the capital gains tax that was scheduled to come into effect in 2013.[3]

Since the objective is to use the joint distribution of income and wealth to identify different modeling components, we adopt a market-based notion of total income that is compatible with the models of income and wealth heterogeneity mentioned in the previous section. Our definition of market income includes wage and salary income, business and farm income, interest and dividend income, private pension withdrawals and capital gains. In particular, we exclude income from fiscal sources such as transfer income and social security income.

[2] Recent work by Fagereng et al. (2016) and Bach et al. (2016) provide empirical evidence for rate of return heterogeneity using panel data from Norway and Sweden, respectively

[3] The Patient Protection and Affordable Care Act enacted in 2010 provided for additional taxes on high income groups starting in 2013.

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

	Top Percentile							
	0.1%	0.5%	1%	5%	10%	20%	40%	Gini
Earning Share	0.06	0.13	0.18	0.36	0.48	0.65	0.86	0.58
Income Share	0.08	0.18	0.23	0.41	0.53	0.68	0.86	0.67
Wealth Share	0.14	0.28	0.37	0.63	0.76	0.88	0.97	0.85

Note.– Data comes from SCF 2010 and 2016.

Labor income is defined primarily by the reported wage and salary income, which include pay for work for an employer as well as any salary drawn from an actively managed business. SCF mainly follows the tax filing guidelines for classifying income to its sources. IRS requires all corporations to explicitly report wage and salary for actively involved shareholders. Some business organizations, such as partnerships and sole proprietorships are exempted from this requirement. We impute wage and salary income either if a household reports income from actively owned businesses, but does not report any wage income, or, if the respondent or the spouse reports explicitly that they do not draw salary from their actively managed business. To determine the share of business income that is attributable to capital, we regress active business income on the total value of equity in the active business controlling for the number of hours worked by the household members that are actively involved as well as demographic characteristics such as gender, age, education. The resulting coefficient on equity is 0.26, which corresponds to the share of capital. Accordingly, we allocate 74 percent of active business income to labor for those who do not report wage income from their business.

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 0.85, whereas it is 0.58 for earnings and 0.67 for income. This is driven by both the heavier concentration of wealth at the top, as well as a larger fraction of households with no assets relative to those with no income. The top 1% of the net worth distribution has 37% of all assets, while the highest income groups earn about 23% of all income. Wage and salary income has a similar concentration with the top 1% earners' share of 18% in all earnings.

There is a strong correlation between wealth and earnings in the data. This can be seen in Table 2 that shows the wealth shares of different earnings and income groups. The top 1% of highest earners have about 19% of total wealth. Similarly, highest 1% of incomes represent 27% of total wealth in the U.S.. A correlation of zero would imply wealth shares that are equal to the population shares when ranked by income or earnings. The coefficient of correlation between earnings and net worth is 0.27 and it is 0.52 between income and net worth, suggesting that earnings potentially play a significant role for accumulation of wealth.

Table 3 shows the factor composition of income for top income groups. The first panel shows the fraction of wage and salary income in total income as reported by the households. The second panel shows the total income from labor, including imputed wage and salary for households who do not draw explicit wage income from their actively managed businesses. Each definition is reported with and without capital gains. On the aggregate, 74 to 84 percent of net income is attributed to labor.[4] Most households rely primarily on wage

[4]Since the accounting convention is to report the net income from capital, i.e. excluding depreciation, the share of labor in net

Table 2: Shares of Wealth by Income and Earnings

	Top Percentile				
	1%	5%	10%	20%	40%
Wealth by Earnings	0.19	0.37	0.45	0.55	0.65
Wealth by Income	0.27	0.51	0.61	0.71	0.81

Note.– Table shows the share of wealth held by different income and earnings groups. Data comes from SCF 2010 and 2016.

Table 3: Labor Component of Income

	All	Top Income Groups		
Percentile	0-100	90-95	95-99	99-100
Wage Income				
with capital gains	74	83	69	49
without capital gains	78	84	73	56
Labor Income				
with capital gains	80	76	69	59
without capital gains	84	80	75	68

Note.– Table shows the share of income from labor. Data comes from the 2010 and 2016 waves of the SCF. The first panel shows the reported wage and salary as share of total income including or excluding capital gains. The second panel includes imputed wage income for active business owners who do not draw salary from their businesses.

income. Outside the top 1 percent of the income distribution, labor income constitutes at least two thirds of total income. Since business income and capital gains are not an important source of income for these groups, the particular definition of income does not affect this result. For the top 1 percent of the income distribution, labor income constitutes 59 percent of total income when capital gains are included, and 68 percent when they are excluded from the definition of income. Without imputation of wages for some business owners, the labor share of income is roughly 10 points lower. These results suggest that income from labor is the major source of income for this group, constituting at least a half of total income among top 1 percent of households.

Table 4 compares our findings with the statistics from the IRS data. We use the 2015 update to the tables in Piketty & Saez (2007), 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 business income is reported separately. These figures are comparable to the first panel on Table 3. The share of wage income for the top 1 percent income group as reported by tax units in Table 4 is 49 percent when capital gains are included and 56 percent when they are excluded, same as our findings in the SCF data reported in Table 3.[5] Columns 2 to 5 in Table 4 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, share of wage income drops and interest and dividend income becomes increasingly

income is typically 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.

[5]There are two subtle but apparently inconsequential differences between the two sets of statistics. First, the income concept reported in Piketty & Saez (2007) 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.

Table 4: Composition of Income for Top Income Groups (IRS)

	Income Percentile Category				
w/o KG	99-100	99-99.5	99.5-99.9	99.9-99.99	99.99-100
Wage	56	73	61	47	34
Business	30	20	29	37	37
Interest and Dividend	14	7	10	15	29
	Income Percentile Category				
w KG	99-100	99-99.5	99.5-99.9	99.9-99.99	99.99-100
Wage	49	68	54	40	27
Business	27	19	26	32	30
Interest, Dividend and Capital Gains	24	13	19	28	42

Note.– Figures in percentages and correspond to averages for 2010-2015. Income percentiles are determined excluding capital gains (KG). Figures come from 2015 update to Piketty and Saez (2007)

important. For the top 0.01 percent of the income distribution, interest and dividend income constitutes 42 percent of total income when capital gains are included.

Both the survey data from SCF and the tax data from the IRS records agree on the relative roles of different sources of income. For most households, earned income from labor services is the primary source of income. As we move up the income ladder, 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 at least half the income can be attributed to labor. As the size of the top fractile 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 top 0.1% highest income earners.

4 Model

For the analysis, we employ an overlapping generations life cycle model with idiosyncratic risk in capital and in labor income.

Each period, a continuum of agents enter the economy, with a potential life-span of J periods, subject to survival probabilities $s(j)$ for each age j. The fraction of age group j in total population is denoted by μ_j, with $\mu_{j+1} = s(j)\mu_j$. Total population is normalized to one: $\sum_{j=1}^{J} \mu_j = 1$.

Agents work for the first $J(r)$ periods of their lives, after which they retire. Workers earn income on their labor and on their savings. A worker's labor endowment is given by $z\varepsilon_j$, where z is a stochastic component following a first-order Markov process $F_z(z'|z)$, and ε_j is a deterministic component that captures age-dependent movements in skills, such as work experience. With this endowment, a worker generates a labor income of $wz\varepsilon_j h$, where w is the market wage per skill unit, $h \in [0, 1]$ is hours worked. Income on savings is denoted by rk, where k denotes assets, and r is an idiosyncratic rate of return that follows a Markov process defined by $F_r(r'|r)$. Once retired, agents collect pension, b, and continue to earn income on their assets. 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 level of expenditures, G, pension payments, and other transfers. The government's budget is balanced at all times.

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

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

subject to

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

where $\phi(k) = \phi_1 \left[(k+\phi_2)^{1-\sigma_c} - 1 \right]$ is the utility value of bequeathed assets. The expectation is taken over the future values of labor endowment, z' and the rate of return on assets, r', given the processes F_r and F_z. We assume that the two processes are independent of each other.

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

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

subject to

$$(1+\tau_s)c + k' = y^d(b, rk) + k + Tr$$

The consumption goods are produced by a representative firm using aggregate capital K and total effective labor N. Output is given by a Cobb-Douglas production function: $Y = F(K,N) = \Psi K^\alpha N^{1-\alpha}$.

4.1 Stationary Equilibrium

Let $s = \{j,k,z,r\} \in S$ 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 $w(s)$ and a distribution of agents over the state space $\Gamma_j(s)$, such that

1. Functions $V(s)$, $c(s)$, $k'(s)$ and $h(s)$ solve the consumers' problems.

2. Firms maximize profits.

3. Factor markets clear

$$K = \int k'(j,k,z,r)d\Gamma_{j<J_r}(j,k,z,r) + \int k'(j,k,r)d\Gamma_{j\geq J_r}(j,k,r)$$
$$N = \int z\varepsilon_j h(j,k,z,r)d\Gamma_{j<J_r}(j,k,z,r)$$

4. The government's budget is balanced:

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

5. $\Gamma_j(s)$ is consistent with the policy functions, and is stationary over time.

5 Estimation of the Model

We use the state of the U.S. economy in 2010 to determine the model parameters. To this end, we first choose a set of parameters based on information that is exogenous to the model. Then, we calibrate the remaining parameters so that, in equilibrium, the model economy is consistent with the empirical distributions of earnings, wealth and income. While our approach is broadly consistent with the standard for quantitative macro models with idiosyncratic risk, it has some distinctive elements. From a modeling perspective, the main differences are in the earnings process, where we allow some households the possibility of reaching an extraordinarily high labor productivity level in the spirit of Castañeda, Díaz-Giménez & Ríos-Rull (2003), Kindermann & Krueger (2014) and Kaymak & Poschke (2016), and in the rate of return risk in the spirit of Benhabib, Bisin & Luo (2015). 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. Agents enter the economy at the age of 20, and the first model period ($j = 1$) corresponds to ages 20-24. Death is certain after age $J = 16$, which corresponds to ages 95-99. Retirement is mandatory at age 65 ($j_R = 10$). Following Halliday et al. (2015), we assume that the survival probability is a logistic function of age:

$$s(j) = \frac{1}{1 + \exp(\omega_0 + \omega_1 j + \omega_2 j^2)}$$

The parameters of the survival probability function are calibrated to match three moment conditions suggested by Halliday et al. (2015): the dependency ratio (population aged 65 and over divided by population aged 20-64), which is 39.7% in the data, the death rate weighted by age for 20 to 100 year olds (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 (2.27 in the data). The resulting parameter estimates are reported in Table 6.

Table 5: Labor Productivity Process

	$f_L + a_L$	$f_L + a_M$	$f_L + a_H$	$f_H + a_L$	$f_H + a_M$	$f_H + a_H$	z_7	z_8
$f_L + a_L$	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}

5.2 Preferences

Preferences are described by a discount rate, β, the elasticity of intertemporal substitution, σ_c, the Frisch elasticity of labor supply, σ_l, the disutility of work θ and the parameters that govern utility from bequests: ϕ_1 and ϕ_2. We set $\sigma_l = 1.67$, which implies a Frisch elasticity of 0.6. Blundell, Pistaferri & Saporta-Eksten (2016) report an estimate of 0.4 for males and 0.8 for females. Thus a value of 0.6 for a model of households seems broadly plausible. We choose θ so that at the equilibrium an average household allocates 35% of their time endowment to work. We choose $\sigma_c = 1.5$, in the middle of the range typically used in the literature. The subjective discount factor β is chosen so that, together with the depreciation rate of 8.5%, the capital-to-income ratio is 2.9. This results in a value of $\beta = 0.94$, or an annual discount factor of 0.9885. The implied (value-weighted) interest rate that clears the asset market is 2.56%.

5.3 Income Process

Following Kaymak & Poschke (2016), we assume that labor productivity contains 8 distinct values in increasing order of which the first six are ordinary states and the other two are extraordinary states reserved for exceptionally high earnings levels that are commonly censored in the survey data. The ordinary levels of productivity consist in combinations of two components: a permanent component, $f \in \{f_H, f_L\}$, that is fixed over a household's lifespan, and a random component, $a \in \{a_L, a_M, a_H\}$. Let $A = [A_{ij}]$ with $i, j \in \{L, M, H\}$ be 3-by-3 transition matrices associated with the two components f and a. The invariant distribution of permanent components is taken from Kaymak & Poschke (2016) and individuals randomly draw the value of f from it in the first period. With this formulation, idiosyncratic fluctuations in labor income risk along the life cycle are captured by A. The stochastic labor productivity process is summarized by the matrix in Table 5.

The following additional assumptions are explicit in the formulation of the matrix. The probability of reaching an extraordinary status within lifetime, λ_{in}, is independent of one's current state. Likewise, if a household loses their extraordinary status, then it is equally likely to transition to any ordinary state.[6]

Our working assumption is that the values for ordinary states and the transitions within are directly observed in the data, whereas the transitions to, from and within extraordinary states are not. We jointly calibrate the

[6]The formulation of the transition matrix allows for the possibility of transitioning between different values of the permanent component f by passing through an extraordinary state. However, given the calibrated values for λ_{in} and λ_{out} below, the probability of such an event is extremely small.

levels of ordinary states and the elements of the transition matrix A in order to match the average wage growth of 0.305 log-points observed in the data, the annual autocorrelation of 0.985, as estimated by Krueger, Ludwig et al. (2013), the variance of earnings for working age households, which is reported as 0.75 by Heathcote, Perri & Violante (2010). This leaves the transitional probabilities ($\lambda_{in}, \lambda_{out}, \lambda_{ll}, \lambda_{lh}, \lambda_{hl}, \lambda_{hh}$) and the extraordinary productivity levels z_7, z_8. In order to identify these parameters, we include moments on the marginal distribution of income, specifically, the top 0.5, 1, 5 and 10 percent concentration ratios and the Gini coefficients of inequality, as well as on the persistence of remaining a top 1% earner in the set of target moments for the estimation of the model.

5.4 Capital income process

In addition to the earnings process, we incorporate heterogeneous and stochastic returns to saving in our model in order to better explain wealth concentration at the top. Since asset returns are not directly observed in the data, we include moments on wealth concentration among the set of target moments to identify the levels of returns,$\{r_{H,}r_L\}$, and the diagonal elements of the transition matrix,$\{R_{LL}, R_{HH}\}$.

5.5 Tax system

The tax system consists of personal income taxes levied on capital and labor earnings, corporate taxes and a sales tax. The tax receipts are used 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.[7] We set $\tau_c = 23.6\%$, which is the average effective marginal tax rate on corporate profits in 2010 as reported by Gravelle (2014) based on tax records. To reflect the fact that for most households, positive net worth takes the form of real estate and thus is not subject to corporate income taxes, we assume that corporate taxes only apply to capital income above a threshold d_c.[8] We then choose d_c such that the share of top 1% corporate taxes as a fraction of that group's income is 5.1%, as in the period 2004-2010 (Piketty & Saez 2007).

Personal income taxes are applied to earnings, non-corporate capital income and pension income, if any. Taxable income for income tax purposes is given by:

$$y_f = zw\varepsilon_j h + \min\{rk, d_c\} \qquad \forall j < J_r$$
$$y_f = b + \min\{rk, d_c\} \qquad \forall j \geq J_r$$

Total disposable income is obtained after applying corporate and personal income taxes and adding lump-sum transfers from the government:

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

[7]Corporate income taxes reduce the tax base for personal income tax.
[8]Only about 20% of U.S. households hold stocks or mutual funds directly (Bover (2010), Heaton & Lucas (2000)).

The first two terms above represent our formulation of the current U.S. 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 $0 \leq \tau \leq 1$ controls the degree of progressivity of the tax system, while λ adjusts to meet the government's budget requirement. $\tau = 0$ implies a proportional (or flat) tax system. When $\tau = 1$, all income is pooled, and redistributed equally among agents. For values of τ between zero and one, the tax system is progressive.[9] See Guner et al. (2014), Heathcote et al. (2017a) and Bakış et al. (2015) for evidence on the fit of this function.

One advantage of this formulation for the income tax system is that it also allows for negative taxes. Income transfers are, however, non-monotonic in income. When taxes are progressive, transfers are first increasing, and then decreasing in income. This feature allows addressing features of the real tax system like the earned income tax credit and welfare-to-work programs, which imply transfers that vary with income.

When disposable income is log-linear in pre-tax income, the marginal tax rate increases monotonically with income, converging to 100% at the limit. The second term in the maximum operator avoids this feature by imposing a cap on the top marginal tax rate, denoted by τ_{max}. y_b denotes the critical level of taxable income at which the top marginal tax rate is reached: $\lambda(1-\tau)y_b^{-\tau} = 1 - \tau_{max}$. The top marginal tax rate in 2013 is set to 39.6%, as reported by the IRS. For identification of the progressivity of the general income tax system, τ, we include the observed difference between the average income tax rate for the top 1% and 99% of the income distribution as reported by Piketty & Saez (2007) among the set of target moments. The resulting value is 6.8%.

The government uses the tax revenue to finance exogenous expenditures, pension payments and transfers. The expenditures are set at 6.3% of GDP to yield a sum of expenditure and transfers of 16.33% of GDP, as observed in the data. In addition, the government makes lump-sum transfers to all households. In the data, these transfers represent 2.7% of GDP in the form of disability benefits, veterans benefits etc. We set the transfers in the model Tr accordintly. In the last step, we choose λ in the personal income tax function to balance the government's budget.

5.6 Bequests

The model does not feature an explicit link between parents and their off-springs, which requires larger state space, and is computationally challenging. On the other hand, redistribution of all bequests among younger agents, a common simplification, curbs the model's ability to capture the dynastic persistence of wealth. We proceed with a hybrid approach, which can be summarized as follows. We assume that agents randomly draw a bequest when they reach the age of 50 from the actual bequest distribution of the deceased in the model. All agents know that they will receive a bequest, and know the distribution they will draw from, but have no information about their parents' specific state variables and therefore cannot exactly infer the size of the bequests that they are likely to receive. Instead, they know the permanent earning type of their parents, and draw from the corresponding bequest distribution. More precisely, there are two types of parents and children, who are high and low productivity. High productivity agents have a higher chance of having high productivity parents.

[9] The average income tax rate is $1 - \lambda y^{-\tau}$, which increases in y if $\tau > 0$.

Table 6: Calibration of the Model: Preset Parameters

Parameter	Description	Value	Source
		Demographics	
J	Maximum life span	16	
j_R	Mandatory retirement age	10	
s_0, s_1, s_2	Survival probability by age	-5.49, 0.15, 0.016	Halliday et al. (2015)
α	Share of capital	0.33	
		Preferences	
σ_c	Risk aversion	1.5	
σ_l	Frisch elasticity	1.22	Blundell et al. (2016)
$\{\varepsilon_j\}_{j=1}^{j_R-1}$	Age-efficiency profile		Conesa et al. (2009)
$\{z_1, ..., z_6\}$	Ordinary productivity states		Kaymak & Poschke (2016)
A_{ij}	Transition rates of ordinary productivity		Kaymak & Poschke (2016)
τ_c	Marginal corporate tax rate	0.236	Gravelle (2014)
τ_s	Consumption tax rate	0.05	Kindermann & Krueger (2014)
Tr	Government transfers/GDP	2.7%	Kaymak & Poschke (2016)

Table 7: Calibration of the Model: Jointly Calibrated Parameters

Parameter	Description	Value	Parameter	Description	Value
β	Annual Discount rate	0.97	χ	Labor disutility	7.0
$\lambda_{in}, \lambda_{ll}, \lambda_{lh}, \lambda_{hh}$	Transition rates	Table 12	z_7, z_8	Top productivity states	Table 12
R_{LL}, R_{HH}	Transition rates	Table 14	r_L, r_H	Levels of rate of return	Table 14
ϕ_1, ϕ_2	Bequest utility	-1.42, 1.99	Ψ	Production technology	1.62
τ_l	Tax progressivity	4.3%	d_c	Corporate asset threshold	1.11
κ	Pension / Earnings	0.42	G/Y	Expenditures / GDP	6.3%
δ	Depreciation	6.5%			

As a result, agents with higher earnings and wealth are, on average, likely to receive larger bequests. This setup allows for dynastic wealth accumulation across generations, while limiting the state space to a computationally feasible level.

The parameters of the utility function for bequests are chosen to match the bequest-to-wealth ratio reported by Guvenen, Kambourov, Kuruscu, Ocampo & Chen (2015) and the 90th percentile of the bequest distribution normalized by income reported in De Nardi & Yang (2014).

Table 6 shows the resulting values for parameters that are calibrated outside the model. Table 7 presents the parameters estimates and Table 8 presents a list of targeted moments.

5.7 Calibration Results

In this section we discuss the fit of the model to the distributions of earnings, income and wealth, followed by a discussion of earnings and rate of return processes implied by the calibration. We also compare the model's implications for the evolution of earnings, income and assets over the life-cycle. Tables 7 and 8 provide a summary

Table 8: Summary of Target Moments

Moment	Source	Data Value	Model Fit	Moment	Source	Data Value	Model Fit
Mean hours worked		0.35	0.34	Soc. Sec. Pay / GDP	NIPA 2010	8.1%	7.2%
Top 0.5%,1%,5%,10% income shares	SCF 2010	Table 9	Table 9	Gini coefficient of income	Heathcote et al. 2010	0.67	0.60
Top 0.5%,1%,5%,10% wealth shares	SCF 2010	Table 9	Table 9	Gini coefficient of wealth	SCF 2010	0.85	0.86
Bequest/Wealth	Guvenen et al.(2017)	1-2%	1.54%	90th pct bequest dist.	De Nardi et al. (2014)	4.53%	4.27%
Difference between average income tax rate for top 1% and 99%	Piketty and Saez (2007)	6.8%	6.8%	Corporate income tax revenue/GDP	NIPA	2.5%	2.4%
Probability of staying in top1% earnings share	SCF2010	0.58	0.50				
Overall labor income share	SCF	0.79	0.79	Top 1% labor income share	SCF	0.58	0.65
P95-99 labor income share	SCF	0.74	0.77	P90-95 labor income share	SCF	0.85	0.78

Table 9: Distributions of wealth, earnings and income

	Top Percentile							
	0.1%	0.5%	1%	5%	10%	20%	40%	Gini
Wealth Share (Data)	0.14	0.28	0.37	0.63	0.76	0.88	0.97	0.85
Wealth Share (Model)	0.07	0.26	0.39	0.65	0.76	0.88	0.98	0.86
Earning Share (Data)	0.06	0.13	0.18	0.36	0.48	0.65	0.86	0.58
Earning Share (Model)	0.05	0.17	0.20	0.30	0.40	0.53	0.73	0.48
Income Share (Data)	0.08	0.18	0.23	0.41	0.53	0.68	0.86	0.67
Income Share (Model)	0.05	0.19	0.23	0.36	0.46	0.63	0.81	0.60

Note.- Data comes from SCF 2010 and 2016. The income Gini are for whole population, both in the model and in the data.

Table 10: Joint Distribution of Income and Wealth

	Top Percentile						
Income group	1%	5%	10%	20%	40%	60%	80%
Data	0.27	0.51	0.61	0.71	0.81	0.87	0.94
Model	0.35	0.50	0.62	0.70	0.79	0.87	0.95
Earning group	1%	5%	10%	20%	40%	60%	80%
Data	0.19	0.37	0.45	0.55	0.65	0.71	0.77
Model	0.22	0.28	0.37	0.41	0.52	0.60	0.65

Note.– Table shows the shares of wealth held by different pre-tax income and earning groups. Data values come from SCF 2010.

of parameter estimates and target moments.

Table 9 shows the cross-sectional distributions of the key variables in the model. The targeted moments are shown in red. The model does a good job of capturing the distributions.

The model captures the strong connection between income and wealth with a correlation coefficient of 0.5 compared to 0.54 observed in the data. Table 10 shows the distribution of wealth by income and earnings groups. The share of wealth held by the top 1% income group is 0.35, while it is 0.50 for the top 5% income group. These are somewhat higher than the 24% and 48% observed in the data despite the slightly lower correlation coefficient overall. The top 1% earnings group hold about 22% of wealth, compared to 19% in the data.

The correlation between income and wealth is governed by savings rates of different income groups as well as the rate of return on their savings. Therefore, a model could potentially generate a high correlation between income and wealth by prescribing either a substantially high rate of return for top income groups or a high savings rate. While we do not observe the distribution of rates of return on assets for the U.S., the literature has constructed synthetic saving rates for different wealth groups. To check if the model prescribed role for the two factors are in line with the data, we replicate the synthetic savings rates in the model and report them in Table **??**. The predictions differ slightly for the bottom 90% of the distribution, where the synthetic saving rates in the data are zero, whereas, that in the model is 8%. Nonetheless the model predicts saving rates that are strongly

Table 11: Share of Income from Labor

	All	Top(%)			Quintiles				
	0-100	99-100	95-99	90-95	5th	4th	3rd	2nd	1st
Data	0.79	0.58	0.74	0.85	0.74	0.90	0.89	0.79	-0.37
Model	0.79	0.65	0.77	0.78	0.77	0.88	0.83	0.76	0.07

Table 12: Productivity Transitions in the Model

	1.00	1.88	3.53	2.98	5.61	10.53	97.37	142.81
1.00	0.874	0.119	0.004	0	0	0	0.002	0
1.88	0.060	0.879	0.060	0	0	0	0.002	0
3.53	0.004	0.119	0.874	0	0	0	0.002	0
2.98	0	0	0	0.874	0.119	0.004	0.002	0
5.61	0	0	0	0.060	0.879	0.060	0.002	0.0
10.53	0	0	0	0.004	0.119	0.874	0.002	0.0
97.37	0.029	0.029	0.029	0.029	0.029	0.029	0.802	0.026
142.81	0	0	0	0	0	0	0.168	0.832
Invariant Dist.	0.124	0.246	0.124	0.124	0.246	0.124	0.013	0.002

increasing in wealth, in line with data.

Next we compare the model's fit for the factor composition of income for different income groups. Table 11 shows the share of labor earnings in total income for various income groups. The model generates a high share of labor income for the top 1% as observed in the data. This share is especially high for the lower deciles, with the exception of second and third quintiles. The reason for this is the high concentration of pension income in the model relative to the data.

The transition matrix for the earnings process and the earnings levels implied by the calibration procedure is shown in Table 12. The lowest earnings level is normalized to 1. The top two (extraordinary) earnings states represent 1.3% of the population. The earnings distribution implied by the wage process is similar to the one observed in the data: the ratios of average earnings in the top 5%, 0.1% and 0.01% of earners to the median earnings are 5, 34 and at most of the order of 200 in the data from WWID relative to 8, 64 and 72 in the model. Given the limited number of top earnings states, the model undershoots the highest earnings levels in the data and overshoots the next highest category. Given the transition probabilities, the probability of remaining in the top 1% of earnings from one year to the next is 50.5%, compared to the target moment of 58% used in the estimation.

Table 13 below compares summary moments of the distribution of earnings growth implied by the model with those reported in Guvenen, Karahan, Ozkan & Song (2015) based on data from the Social Security Administration. Overall, the estimated earning process captures the basic properties fairly well, in particular the high kurtosis observed in the data.

The levels of rates of returns on assets and the corresponding transition matrix is shown in Table 14. Since, correspnding data is not available for the U.S., we compare the calibrated returns with those obtained for Norway as reported in Fagereng et al. (2016). The average rate of return observed in the Norwegian data is 3.2% with a

Table 13: Distribution of Earnings Growth for the Top 1% of Earners

Moment	std. dev.	skewness	kurtosis
SSA Data	1.7	-1.3	8.3
Model	2.0	-2.9	10.4

Note.– Data moments come from Guvenen, Karahan, Ozkan & Song (2015), and are based on Social Security Administration data.

Table 14: The Transition Matrix for the Rate of Return on Assets

	2.54%	7.30%
2.54%	0.817	0.183
7.30%	0.198	0.802
Invariant Dist.	0.520	0.480

standard deviation of 5.3% across households. In the model, the average rate of return is 2.4% with a standard deviation of 2.1%.

5.8 Implications for Life-Cycle Dynamics

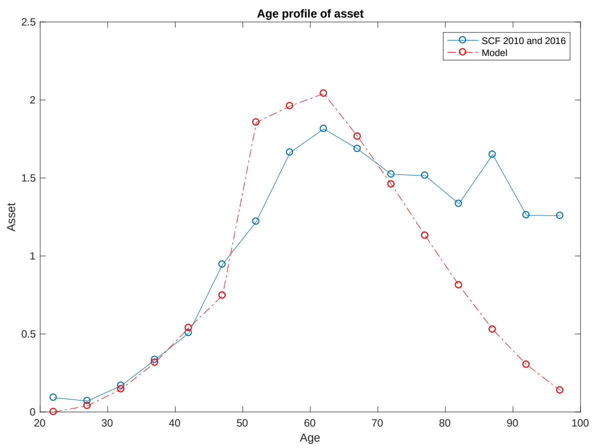
Next, we analyze the model's implications for the evolution of income and wealth over the life-cycle, and compare it with the data. Note that age-dependent distributions of income and wealth are not specifically targeted in the calibration. Therefore, this analysis provides an overidentification test of our model.

Figure 1 shows average earnings, income and wealth by age group in the model and compares it with data from the SCF. The productivity process is calibrated to match the observed wage profile by age in the data. The earnings profile depicted in Figure 1c is a result of households' labor supply decisions given the wages. This is the primary source of income for young households as their assets are initially close to zero. With age, households accumulate assets, and start generating investment income. Average wealth increases up until the retirement age. After retirement, agents rely only on capital income, and start consuming out of their savings. The model accurately captures the salient features of the life-cycle dynamics of income and wealth. That the calibration of the model closely replicates these patterns demonstrates its ability to accurately capture the labor supply and savings behavior among households.

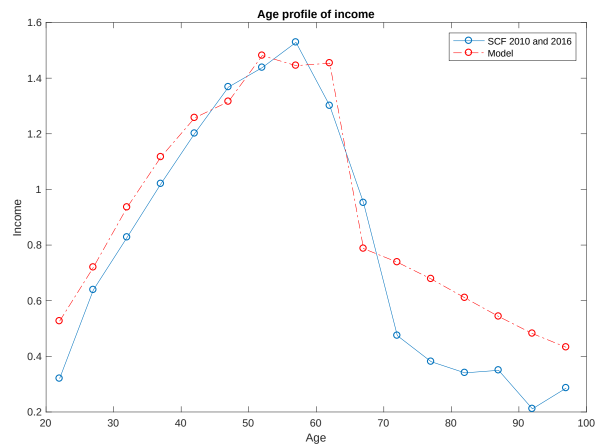
Figure 2 shows the evolution of the dispersion of earnings, income and wealth in the model in comparison with the data. The rise in the dispersion of earnings is governed by the productivity process described in Table 12. The earnings inequality grows mainly because the wages of young households are closer to each other. With age, some households move to higher earnings states, and some to top earnings states. The Gini for wealth is initially very high. This is because households have little assets and weak saving motives initially in anticipation of growing earnings profiles. Ideally, they would have preferred to borrow to smooth their consumption over the life-cycle if it weren't for the borrowing constraint. The presence of many households without assets delivers a high Gini coefficient. With age, earnings grow and retirement approaches. As a result asset accumulation becomes more prevalent among households. This reduces the Gini coefficient in the first part of the life-cycle.

Figure 1: Average Earnings, Income and Assets over the Life-Cycle

(a) Assets



(b) Income



(c) Earnings

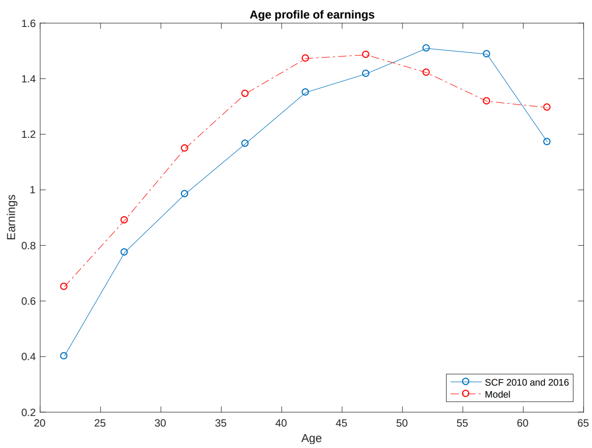
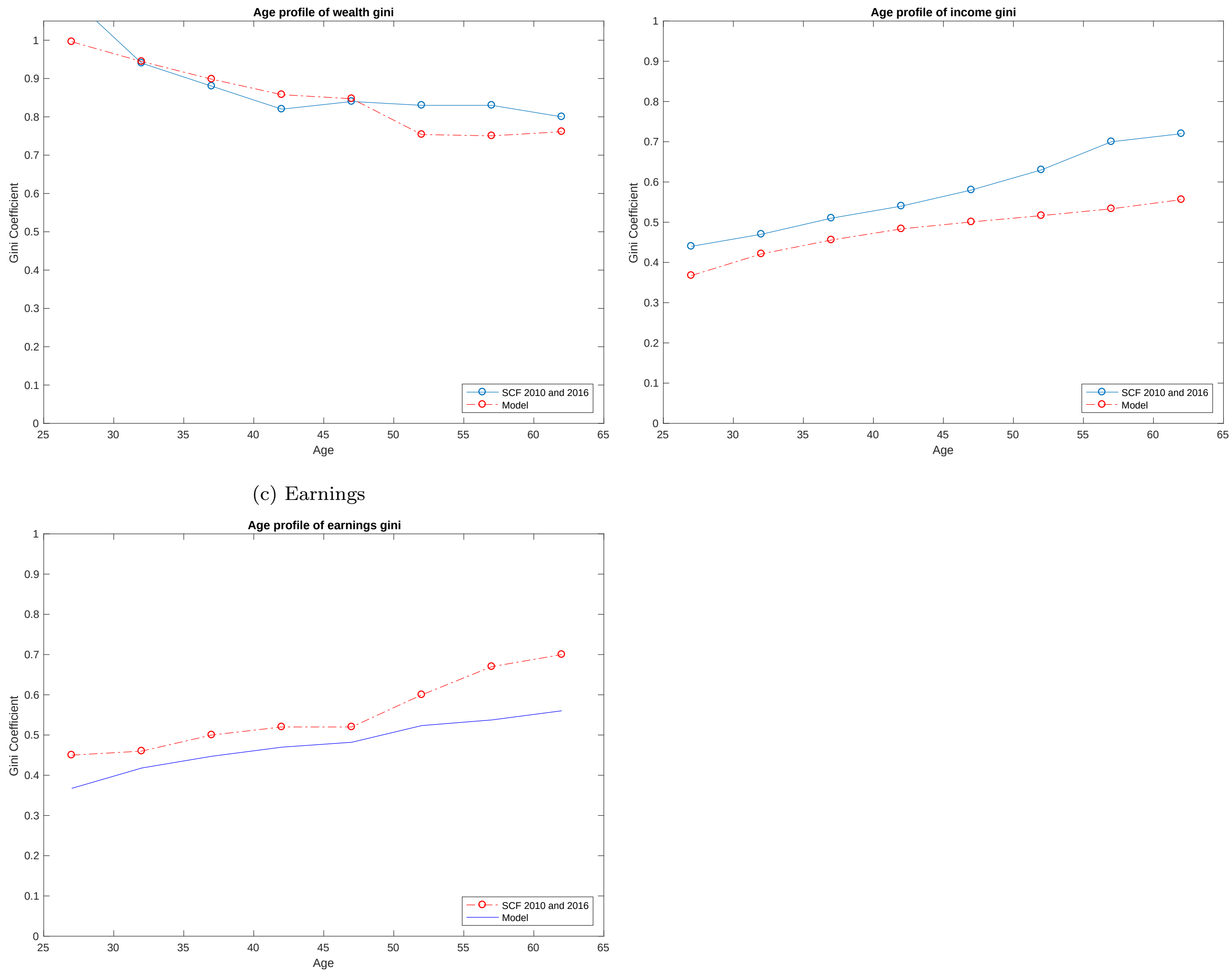


Figure 2: Gini Coefficients for Earnings, Income and Assets Inequality over the Life-Cycle

(a) Assets

(b) Income

(c) Earnings



About 15-20 years after market entry, the reduction in wealth Gini is counteracted by the increasing dispersion in earnings and income, which raises the wealth inequality. These two forces are more or less equivalent, resulting in a stable dispersion of wealth for middle aged households and older, as in the data.

6 Determinants of Wealth Distribution

In this section, we simulate counterfactual economies to assess the relative roles of different factors in explaining the dispersion of wealth in the U.S.. We conduct two exercises. First, we conduct a decomposition exercise where we eliminate each factor individually from the model and study the implied wealth distribution, using the parameters from the benchmark calibration. This allows us to gauge the contribution of each factor to wealth concentration. In a second exercise, we eliminate each factor individually, but recalibrate the model to replicate the observed top 1% wealth share in the data. Studying the implications of this exercise for the joint distribution

Table 15: Determinants of Wealth Concentration without recalibration

	Top Percentile						
Wealth Share	0.01%	0.1%	0.5%	1%	5%	10%	Gini
Benchmark	0.018	0.105	0.259	0.373	0.604	0.706	0.837
No top earners	0.001	0.012	0.050	0.088	0.272	0.426	0.674
No het. return	0.016	0.098	0.247	0.359	0.592	0.694	0.830
No bequest	0.014	0.073	0.199	0.290	0.496	0.615	0.785
Take away all	0.001	0.010	0.045	0.081	0.254	0.405	0.659
Income Share	0.01%	0.1%	0.5%	1%	5%	10%	Gini
Benchmark	0.012	0.049	0.143	0.174	0.274	0.358	0.458
No top earners	0.001	0.006	0.028	0.052	0.150	0.245	0.362
No het. return	0.011	0.047	0.137	0.163	0.265	0.341	0.453
No bequest	0.011	0.044	0.132	0.160	0.260	0.344	0.453
Take away all	0.001	0.006	0.028	0.050	0.141	0.228	0.353

of earnings, income and wealth allows us to highlight the main identification mechanisms in our calibration.

Table 15 shows results for wealth and income concentration from the first decomposition exercise. Each row takes away one critical component, and reports the resulting income and wealth shares in the counterfactual economy. The last row in each panel takes away all components.

We remove the top earning states by setting $\lambda_{in} = 0$. This preserves the wage distribution in the bottom four productivity states, and eliminates the two high-productivity states. In this scenario, both income and wealth concentration falls dramatically. The top 1% wealth share falls by more than three quarters. Higher shares fall by even more, with the top 0.01% share falling almost all the way to zero. Since results without top earners are almost identical to those without any of the three channels, it is clear that this is the most important channel by far in generating top wealth concentration.

Eliminating heterogeneous returns by setting r_H and r_L to equal r leads to a small reduction in top wealth shares, in particular at the top. However, the top 0.01% share falls only by a bit more than 10%, from 1.8 to 1.6%. This indicates that, although in theory (Benhabib et al. 2011), only heterogeneous returns can lead to a Pareto tail of the wealth distribution that is fatter than that of the earnings distribution – as is the case empirically –, in practice, the presence of top earners may lead to very high concentration of wealth up to the 0.01st percentile.

Finally, eliminating the bequest motive ($\phi_1 = \phi_2 = 0$) also leads to a substantial reduction in top wealth shares.[10]

These preliminary results suggest that the concentration of income is the primary driver of the concentration of wealth. For now, several caveats apply. A further investigation should also focus on the interaction of high incomes and heterogeneous returns, and on the role of the mean and standard deviations of returns, which are both low in our preliminary calibration.

Table 16 shows the results for wealth and income concentration from the second decomposition exercise. The

[10] Note that accidental bequests still occur.

Table 16: Determinants of Wealth Concentration

	Top Percentile						
Wealth Share	0.01%	0.1%	0.5%	1%	5%	10%	Gini
Benchmark	0.018	0.105	0.259	0.373	0.604	0.706	0.837
No top earners	0.008	0.025	0.073	0.120	0.325	0.482	0.707
No het. return	0.016	0.098	0.247	0.359	0.592	0.694	0.830
No bequest	0.016	0.081	0.215	0.308	0.519	0.639	0.796
Take away all	0.001	0.010	0.045	0.081	0.254	0.405	0.659
Income Share	0.01%	0.1%	0.5%	1%	5%	10%	Gini
Benchmark	0.012	0.049	0.143	0.174	0.274	0.358	0.458
No top earners	0.002	0.010	0.035	0.059	0.177	0.281	0.379
No het. return	0.011	0.047	0.137	0.163	0.265	0.341	0.453
No bequest	0.011	0.050	0.144	0.178	0.284	0.370	0.468
Take away all	0.001	0.006	0.028	0.050	0.141	0.228	0.353

structure of the table is identical to that of the previous table. The difference is that in the case without top earners, the return process is recalibrated to bring the top 1% wealth share back in line with the data. In current results, the model cannot match the top 1% wealth share observed in the data without top earners.

Results in terms of the wealth distribution are similar when the model is recalibrated. Yet, the main results of interest from this exercise are shown in 17: the correlations of income, earnings and wealth and the composition of income for the different cases.

Recall from the previous section that the benchmark model matches these moments closely. The model without top earners or without return heterogeneity could, appropriately recalibrated, in principle still reproduce the observed top wealth concentration. However, it would do so with different correlations of income, earnings, and wealth, and with a different income composition of top income earners. In the benchmark, top income households consist of a mix of top earners and wealth households reaping high returns on investments. A highly concentrated wealth distribution could also obtain in the two polar economies: one where the wealthy have saved out of earnings, and top income earners mostly have labor income, or one where the wealthy have earned high returns on investments, and high income households earn a lot of capital income.

The table shows exactly this quantitatively. An economy with highly concentrated wealth but without top earners features an unrealistically low share of labor income among top income households. The larger return dispersion required for generating wealth concentration in this setting also leads to a significant drop in the link between in earnings and wealth. The correlation between wealth and income increases by about 12 percent. This increase remains limited relative to the decline in the correlation between earnings and wealth, because, on the one hand, top incomes in this scenario are more wealth dependent, but, on the other hand, there is more randomness in the rate of return on the assets.

An economy with homogeneous investment returns, in contrast, features an excessively high labor income share at the top. While the wealth-income correlation hardly changes, the wealth-earnings correlation increases slightly.

Table 17: Key Identifying Moments

	corr(e,w)	corr(y,w)	labor income share for top 1% income households
Benchmark	0.37	0.5	0.71
w/o top earners	0.21	0.56	0.53
w/o ret het.	0.39	0.50	0.77

Note.– Table shows the key correlations from counterfactual economies without rate of return heterogeneity, or without top earners that are re-calibrated to match the wealth concentration in the data.

Taken together, these exercises illustrate how our empirical approach allows identifying the quantitative drivers of wealth concentration. Results are unambiguous: while there is clear evidence of some importance of heterogeneous returns, stemming from the labor income share at the top, overall wealth concentration at the top is mostly driven by the concentration of earnings.

7 Conclusion

Our findings prescribe a significant role for differences in income from labor and earnings risk in explaining the observed dispersion in net worth in the U.S.. This is driven essentially by the large share of wage and salaries in total income for the top income groups. Models that rely solely on differences in capital income across households predict a counterfactually low share of income from labor for top income groups.

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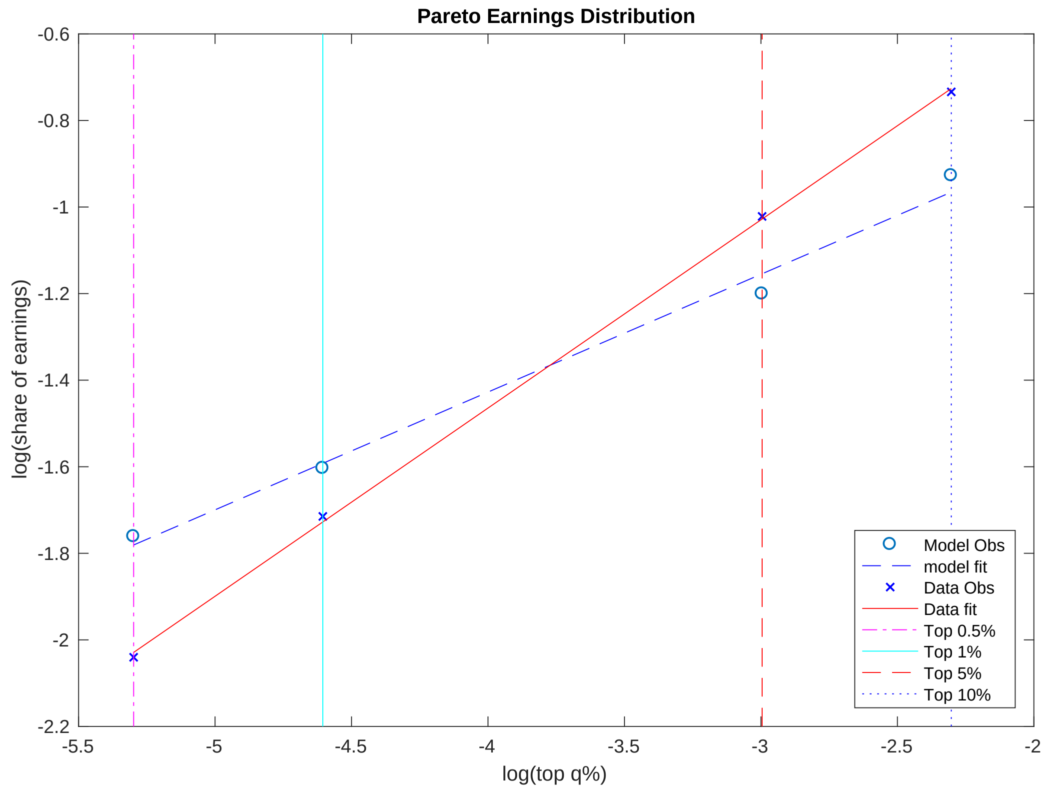
Appendix: Additional Tables and Figures

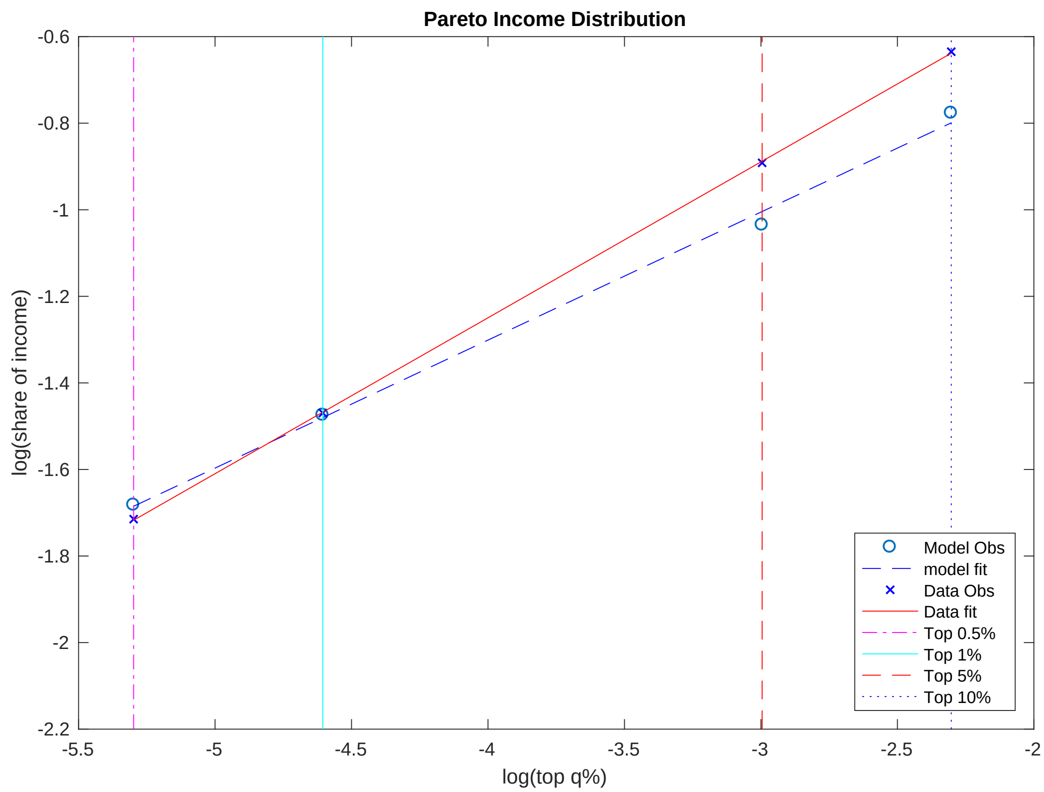
Average tax rates by income group in the benchmark economy

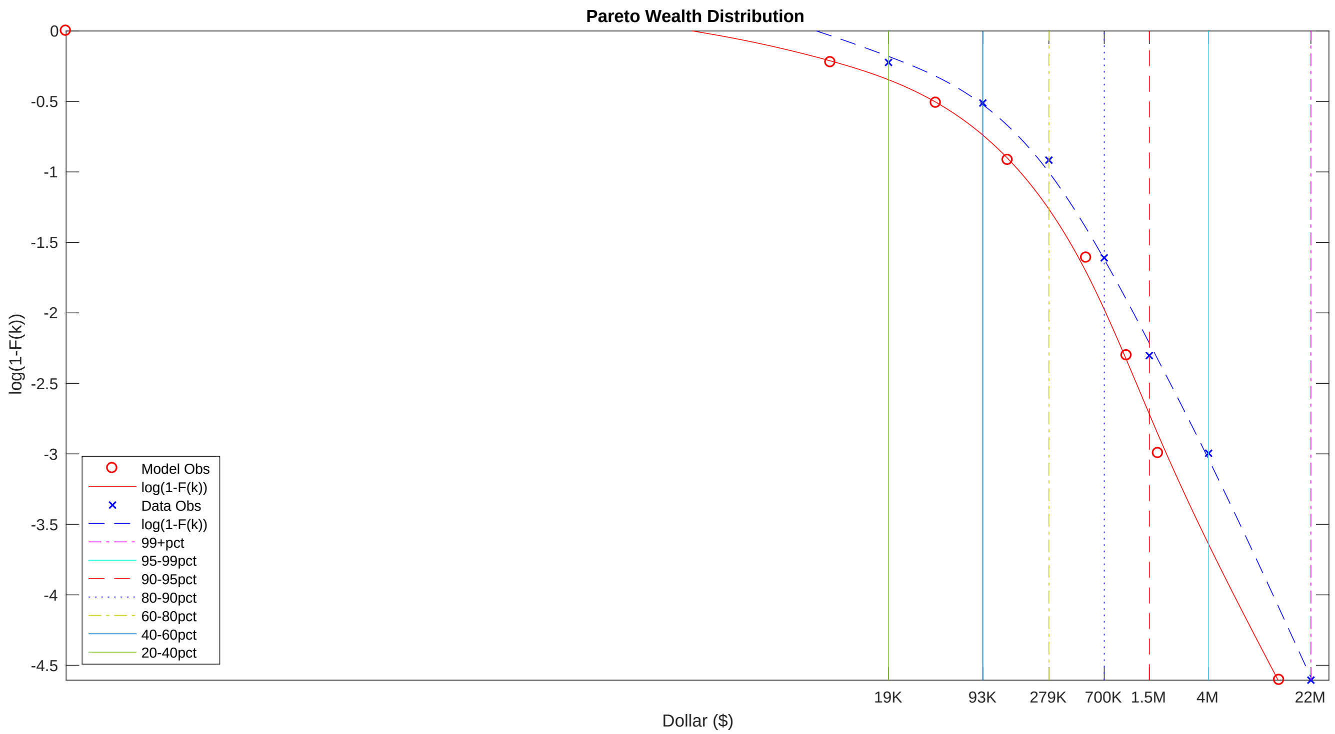
	Corporate tax		Income tax		
	1%	R/GDP	1%	R/GDP	diff. 1% and 99%
Data	4.40%	2.50%	26.73%	16.30%	6.82%
Model	3.79%	2.39%	24.52%	14.20%	6.79%

Table 5: Average Tax Rates by Income Group in the benchmark economy

Pareto Distributions






Pareto Wealth Distribution
log(1-F(k))
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4
-4.5
Model Obs
log(1-F(k))
Data Obs
log(1-F(k))
99+pct
95-99pct
90-95pct
80-90pct
60-80pct
40-60pct
20-40pct
19K
93K
279K
700K
1.5M
4M
22M
Dollar ($)