

Accounting for the determinants of wealth concentration in the US

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Abstract

What are the fundamental determinants of high 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 relevance of each component, and find that labor income differences are the most relevant source of wealth dispersion for most households. Heterogeneity in asset returns are crucial for generating the thick right tail of the wealth distribution for the wealthiest 0.01% of households. The findings are driven by the high correlation between earnings and wealth, and the substantial share of earned income among top income groups observed in the data.

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1 Introduction

The distribution of net worth in the US is highly concentrated. Recent statistics show that 20% of the population hold 87% of all assets, with the wealthiest 1% alone holding 34% of total assets (Kuhn & Ríos-Rull 2016). The recent literature has emphasized a set of factors that can lead to such a high concentration of wealth. The 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, Kaymak & Poschke 2016, Kindermann & Krueger 2014). The 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 (Benhabib et al. 2015, Cagetti & De Nardi 2006, Quadrini 2000). These studies also attribute a non-trivial role to the dynastic accumulation of wealth through bequests (see, for instance, De Nardi (2004)).¹

These approaches differ in their depiction of who the wealthiest are and how they got there. As a result, they can reach quite different conclusions in their assessment of the effects of economic policy. For instance, using a model of labor income uncertainty, Kindermann & Krueger (2014) prescribe 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.

Regrettably, a direct empirical assessment of how important labor and capital income are in generating large fortunes in the US is infeasible due to the lack of a long panel of data on earnings, asset holdings and the rates of return on those assets at the household level. Nonetheless, data is available on the joint 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 earnings

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

and wealth as well as the factor composition of income for top income groups to identify the quantitative importance of rate of return heterogeneity for the wealth distribution in US. This crucial identifying information has not previously been used in the literature on the wealth distribution, which has focussed exclusively on marginal distributions of earnings and wealth.

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 heavy. A version of the model that is estimated using the joint empirical distribution of earnings, income and wealth attributes a non-trivial role to rate of return heterogeneity, especially 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). For most households, however, the dispersion in wealth is driven by differences in earned income and the associated saving rates.

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 US, 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 US. Section 8 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), where 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. the 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 distribution, 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 to generate a Pareto-tailed wealth distribution, a stylized property of the empirical distribution of wealth. 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 households 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 canonical Aiyagari 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 used in the model (Kaymak & Poschke 2016, Kindermann & Krueger 2014). 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 canonical model to generate a realistic wealth distribution for US, presenting 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 US.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 Concentrating on Income and Wealth Concentration

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 sources of data are the Survey of Consumer Finances (SCF), a triennial cross-sectional survey of U.S. families on their assets, income, and demographic characteristics, and various sources in the literature on administrative tax records, which is a cross-sectional source of data on income and

²Recent 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.

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

	Top Percentile							Gini
	0.1%	0.5%	1%	5%	10%	20%	40%	
Earning Share	0.06	0.13	0.18	0.36	0.48	0.65	0.86	0.42
Income Share	0.06	0.12	0.17	0.34	0.45	0.59	0.78	0.43
Wealth Share	0.12	0.25	0.34	0.61	0.74	0.87	0.97	0.85

Note.— Data comes from SCF (2010).

earnings.³

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 0.82, whereas it is around 0.42 for earnings and 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 34% of all assets, while the highest income groups earn about 17% of all income. Wage and salary income has a similar concentration, with the top 1% earners' share making up 18% of all earnings.

There is a strong correlation between wealth and earnings in the data. This can be seen in Table 2, which shows the wealth shares of different earnings and income groups. The top 1% of highest earners have about 20% of total wealth. Similarly, the highest 1% of incomes hold 24% of total wealth in the US. 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 0.53 and it is 0.58 between income and net worth, suggesting that earnings potentially play a significant role for the accumulation of wealth.

Table 3 shows the factor composition of income for different groups. We consider various sources and definitions for what constitutes income from labor. For the SCF, we consider two definitions, a narrow one, that attributes only reported wage and salary income to labor, and considers business income to be entirely capital income. The corresponding values are reported in the first row. Next, we attribute a third of business income to labor, and report the values in the second row. These values are for 2010. An alternative source for these calculations is

³The data sources are Kuhn & Ríos-Rull (2016) for the SCF, and Piketty et al. (2016) and Piketty & Saez (2003). Some of the reported statistics include authors' calculations based on the data reported therein.

Table 2: Shares of Wealth by Income and Earnings

	Top Percentile				
	1%	5%	10%	20%	40%
Wealth by Earnings	0.20	0.41	0.50	0.59	0.69
Wealth by Income	0.24	0.48	0.58	0.70	0.82

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

Table 3: Labor Component of Income

	All	Top(%)			Quintiles				
	0-100	99-100	95-99	90-95	5th	4th	3rd	2nd	1st
SCF 2010: wage income	0.68	0.51	0.71	0.77	0.68	0.77	0.69	0.56	0.41
SCF 2010: wage + 1/3 business	0.75	0.65	0.81	0.83	0.78	0.81	0.71	0.58	0.42
IRS 2000: wage + 1/3 business		0.58	0.74	0.83	0.82	0.85	0.89	0.89	0.88
IRS 2010: wage income		0.57	0.85	0.91					
IRS 2010: wage+ 1/3 business		0.67	0.88	0.93					

Note.— The figures for SCF 2010 are obtained from Kuhn & Ríos-Rull (2016). The figures for IRS are obtained from Guner et al. (2014a) for 2000, and from Piketty & Saez (2003) for 2010.

administrative tax records. In row 3, we report labor’s share of income as reported by Guner et al. (2014a) from IRS records for 2000. They consider a third of business income to be attributable to labor. Piketty & Saez (2003) also report income sources for top income groups in the data addendum to their article. The next two rows report labor income as computed by only wage and salary income, and then including a third of business income, using their data.⁴

While the different sources somewhat disagree on the exact share of labor income due to different definitions of labor income and total income, the following observations can be made for all of them. For most households, earned income from labor services is the primary source of income.⁵ 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

⁴The aggregate labor share does not match the ones typically used in macro models since the accounting convention is to report the net income from capital, i.e. excluding depreciation. Accordingly, we too focus on net capital income in our comparisons of the model predictions below with the data above.

⁵Our reading of the data appendices to these papers suggests that the treatment of pension income and transfers from the government can explain the differences between the rows, especially for income groups below the 90th percentile. We do not expect these to be significant for top income groups.

least half of income can be attributed to labor, even with the most conservative definition of labor income. As the size of the top fractile is reduced, capital income becomes more important. Households in the top 0.1 percent earn 41% of their income in wage and salary, and the top 0.01% earn a third of their income in wage and salary. Adding to that a third of business income, labor income shares remain at 54% and 47%, respectively, for these groups. The upshot of this is that labor income is a major source of income throughout the distribution, 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 $wz\varepsilon_jh$, 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 $\phi(k) = \phi_1 [(k + \phi_2)^{1-\sigma_c} - 1]$ 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: $Y = F(K, N) = AK^\alpha N^{1-\alpha}$.

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

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

4. The government's budget is balanced:

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

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

5 Estimation of the Model

Current results below are preliminary, and are obtained from a calibration exercise.

We use the state of the US 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 described below:

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

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, 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 5.

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 0.5 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 $\sigma_c = 1.5$ to obtain an inter-temporal elasticity of substitution of 0.67. The subjective discount factor β is chosen so that the value-weighted interest rate of 3.7% clears the asset market. This results in a value of $\beta = 0.93$, or an annual discount factor of 0.986.

5.3 Income Process

Following Kaymak & Poschke (2016), we assume that labor productivity contains 6 distinct values in increasing order of which the first four are ordinary states and the other two are extraordinary states reserved for exceptionally high earnings levels that are commonly censored in

Table 4: Labor Productivity Process

	$f_L + a_L$	$f_L + a_H$	$f_H + a_L$	$f_H + a_H$	z_5	z_6
$f_L + a_L$	A_{11}	A_{12}	0	0	λ_{in}	0
$f_L + a_H$	A_{21}	A_{22}	0	0	λ_{in}	0
$f_H + a_L$	0	0	A_{11}	A_{12}	λ_{in}	0
$f_H + a_H$	0	0	A_{21}	A_{22}	λ_{in}	0
z_5	λ_{out}	λ_{out}	λ_{out}	λ_{out}	λ_{ll}	λ_{lh}
z_6	0	0	0	0	λ_{hl}	λ_{hh}

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, $a \in \{a_L, a_H\}$. Let $A = [A_{ij}]$ with $i, j \in \{L, H\}$ be 2-by-2 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 following matrix summarizes the stochastic labor productivity process:

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 All the households are assumed to start their career at a_L . This helps generate wage growth over the life cycle. It is also consistent with a higher variance of wages for older workers.

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 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

⁶The 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.

productivity levels z_5, z_6 . In order to identify these parameters, we include moments on the marginal distribution of earnings, 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 2007a).

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:

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

⁷Corporate income taxes reduce the tax base for personal income tax.

⁸Only about 20% of U.S. households hold stocks or mutual funds directly (Bover (2010), Heaton & Lucas (2000)).

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

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

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. (2014b), Heathcote et al. (2014b) and Bakış et al. (2015a) 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. This is undesirable since an increase in top income levels is mechanically accompanied by higher marginal tax rates. 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 2010 is set to 35%, 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 (2007b) among the set of target moments. The resulting value is 0.15, close to the estimate of progressivity reported in Bakis et al. (2015b) and Heathcote et al. (2014a).

The government uses the tax revenue to finance exogenous expenditures and transfers. The

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

expenditures are set at 5.9% 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, transfers to person represent 2% of GDP in the form of disability benefits, veterans benefits etc. We set the transfers in the model Tr to match receipts per person. In the last step, we choose λ in the personal income tax function to balance the government's budget.

5.6 Bequests

Given the potential importance of bequests for wealth concentration, we depart from the commonly made assumption in life cycle models that bequests are distributed equally in the population.¹⁰ To do so, we assume that at age 50, each child draws a bequest from the actual bequest distribution in the model. In addition, higher-earning children on average receive larger bequests.

To keep the state space limited, we proceed as follows. We assume that all children know that they will receive a bequests at age 50, 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. More precisely, there will be two types of parents and children, who are high and low productivity. High productivity children have a larger chance of having high productivity parents. This assumption preserves a feature of intergenerational transfer of assets. However, the amount of bequest received is randomly drawn from the distribution of the type of parents that the child belongs to. Bequest parameters 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 Nardi & Yang (2014).

Table 5 shows the resulting values for parameters that are calibrated outside the model. Table 6 presents the parameters estimates and Table 7 presents a list of targeted moments.

¹⁰**Examples, exceptions.**

Table 5: Calibration of the Model: Preset Parameters

Parameter	Description	Value	Source
<i>Demographics</i>			
J	Maximum life span	16	Age 95-99
j_R	Mandatory retirement age	10	Age 65-69
s_0, s_1, s_2	Survival probability by age	-5.49, 0.15, 0.016	Halliday et al. (2015)
<i>Preferences</i>			
σ_c	Risk aversion	1.5	Kaymak & Poschke (2016)
σ_l	Frisch elasticity	1.67	
<i>Labor Productivity</i>			
$\{\varepsilon_j\}_{j=1}^{j_R-1}$	Age-efficiency profile		Conesa et al. (2009)
$\{z_1, ..., z_4\}$	Ordinary productivity states		Kaymak & Poschke (2016)
A_{ij}	Idiosyncratic fluctuations in labor income risk		Kaymak & Poschke (2016)
<i>Taxes and Transfers</i>			
τ_c	Marginal corporate tax rate	0.236	Gravelle (2014)
τ_s	Consumption tax rate	0.05	Kindermann & Krueger (2015)
Tr	Government transfers	0.02	NIPA

Table 6: Calibration of the Model: Jointly Calibrated Parameters

Parameter	Description	Value	Parameter	Description	Value
β	Discount rate	0.95	χ	Labor disutility	14
$\lambda_{in}, \lambda_{ll}, \lambda_{lh}, \lambda_{hh}$	Transition rates	Table 12	z_5, z_6	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	-19.6, 39.9	A	Production technology	1.53
τ_l	Tax progressivity	0.15	d_c	Corporate asset threshold	10.1
κ	Pension / Earnings	0.45	G/Y	Expenditures / GDP	5.9%

Table 7: Summary of Target Moments

Moment	Source	Data Value	Model Fit	Moment	Source	Data Value	Model Fit
Mean hours worked				Soc. Sec. Pay / GDP	NIPA 2010	8.1%	8.3%
Top 0.5%,1%,5%,10% earning shares	SCF 2010	0.35 Table 11	0.34 Table 11	Gini coefficient of earnings	Heathcote et al. 2010	0.42	0.42
Top 0.5%,1%,5%,10% wealth shares	SCF 2010	Table 11	Table 11	Gini coefficient of wealth	SCF 2010	0.85	0.82
Bequest/Wealth	Gruenen et al.(2017)	1-2%	1.64%	90th pct bequest dist.	De Nardi et al. 2014	4.53%	4.51%
Difference between average income tax rate for top 1% and 99%	Piketty and Saez (2007)	6.8%	7%	Average corporate tax rate for top 1%	Piketty and Saez (2007)	5.1%	6.19%
Probability of staying in top1% earnings share	SCF2010	0.58	0.66				
Top 1% labor income share	WWID	0.40	0.57	P95-99 labor income share	WWID	0.55	0.62

Table 8: Distributions of wealth, earnings and income

	Top Percentile							
	0.1%	0.5%	1%	5%	10%	20%	40%	Gini
Wealth Share (Data)	0.12	0.25	0.34	0.61	0.74	0.87	0.97	0.85
Wealth Share (Model)	0.12	0.27	0.37	0.59	0.69	0.83	0.97	0.82
Earning Share (Data)	0.06	0.13	0.18	0.36	0.48	0.65	0.86	0.42
Earning Share (Model)	0.04	0.11	0.14	0.24	0.31	0.45	0.70	0.42
Income Share (Data)	0.06	0.12	0.17	0.34	0.45	0.59	0.78	0.43
Income Share (Model)	0.05	0.13	0.17	0.28	0.37	0.50	0.74	0.46

Note.- Data comes from SCF 2010. The income and earnings Ginis are from Heathcote et al. (2010) and refer to 2005, the latest year for which they report results. The income Gini are for working-age households, both in the model and in the data.

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 6 and 7 provide a summary of parameter estimates and target moments.

Table 8 shows the cross-sectional distributions of the key variables in the model. The targeted moments are shown in bold. 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 0.58 (spot on). Table 9 shows the distribution of wealth by income and earnings group. The share of wealth held by the top 1% income group is 0.31, compared to 0.24 in the data. The wealth shares of highest income groups are slightly higher than observed 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 US, 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 10. The predictions differ slightly for the bottom 90% of the distribution, where the

Table 9: Joint Distribution of Income and Wealth

Income group	Top Percentile						
	1%	5%	10%	20%	40%	60%	80%
Data	0.24	0.48	0.58	0.70	0.82	0.91	0.96
Model	0.31	0.51	0.59	0.68	0.85	0.97	0.99
Earning group	1%	5%	10%	20%	40%	60%	80%
	1%	5%	10%	20%	40%	60%	80%
Data	0.20	0.41	0.50	0.59	0.69	0.75	0.88
Model	0.20	0.30	0.35	0.42	0.61	0.75	0.77

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

Table 10: Synthetic saving rates by wealth (percent)

Wealth group	All	Bottom 90%	Top 10%	Top 5%	Top 1%	Top 0.1%
Data (2010)	9	0	24	22	35	44
Model	9	7	13	16	24	32

Note.— Data source: Saez and Zucman (2016) Appendix Table B33

synthetic saving rates in the data are zero, whereas, that in the model is 7%. Nonetheless the model predicts saving rates that are strongly 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 calibra-

Table 11: Share of Income from Labor

	All	Top(%)				Quintiles				
	0-100	99-100	95-99	90-95	5th	4th	3rd	2nd	1st	
Data	—	0.58	0.74	0.83	0.82	0.85	0.90	0.89	0.88	
Model	0.65	0.54	0.58	0.72	0.68	0.83	0.30	0.39	0.83	

Table 12: Productivity Transitions in the Model

	1	2.9	4.0	11.7	61.0	225.4
1	0.989	0.009	0	0	0.002	0
2.9	0.006	0.992	0	0	0.002	0
4.0	0	0	0.989	0.009	0.002	0
11.7	0	0	0.006	0.992	0.002	0
61.0	0.046	0.046	0.046	0.046	0.789	0.027
225.4	0	0	0	0	0.192	0.808
Invariant Dist.	0.209	0.284	0.209	0.284	0.012	0.002

Table 13: Distribution of Earnings Growth

Moment	std. dev.	skewness	kurtosis
SSA Data	1.7	-1.3	8.3
Model	1.4	-2.7	9.5

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

tion procedure is shown in Table 12. The lowest earnings level is normalized to 1. The top state represents 1.4% of the population. The average earnings in these states relative to the lowest state are 61 and 225. This generates a probability of remaining in the top 1% of earnings from one year to the next of 66%, compared to the target moment of 58% used in the estimation.

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

The levels of rates of returns on assets and the corresponding transition matrix is shown in Table 14. Since, corresponding data is not available for US, 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 standard deviation of 5.3% across households. In the model, the average rate of return is 2.7% with a standard deviation of 2.9%.

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

	1.05%	8.02%
1.05%	0.817	0.183
8.02%	0.326	0.674
Invariant Dist.	0.640	0.360

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

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

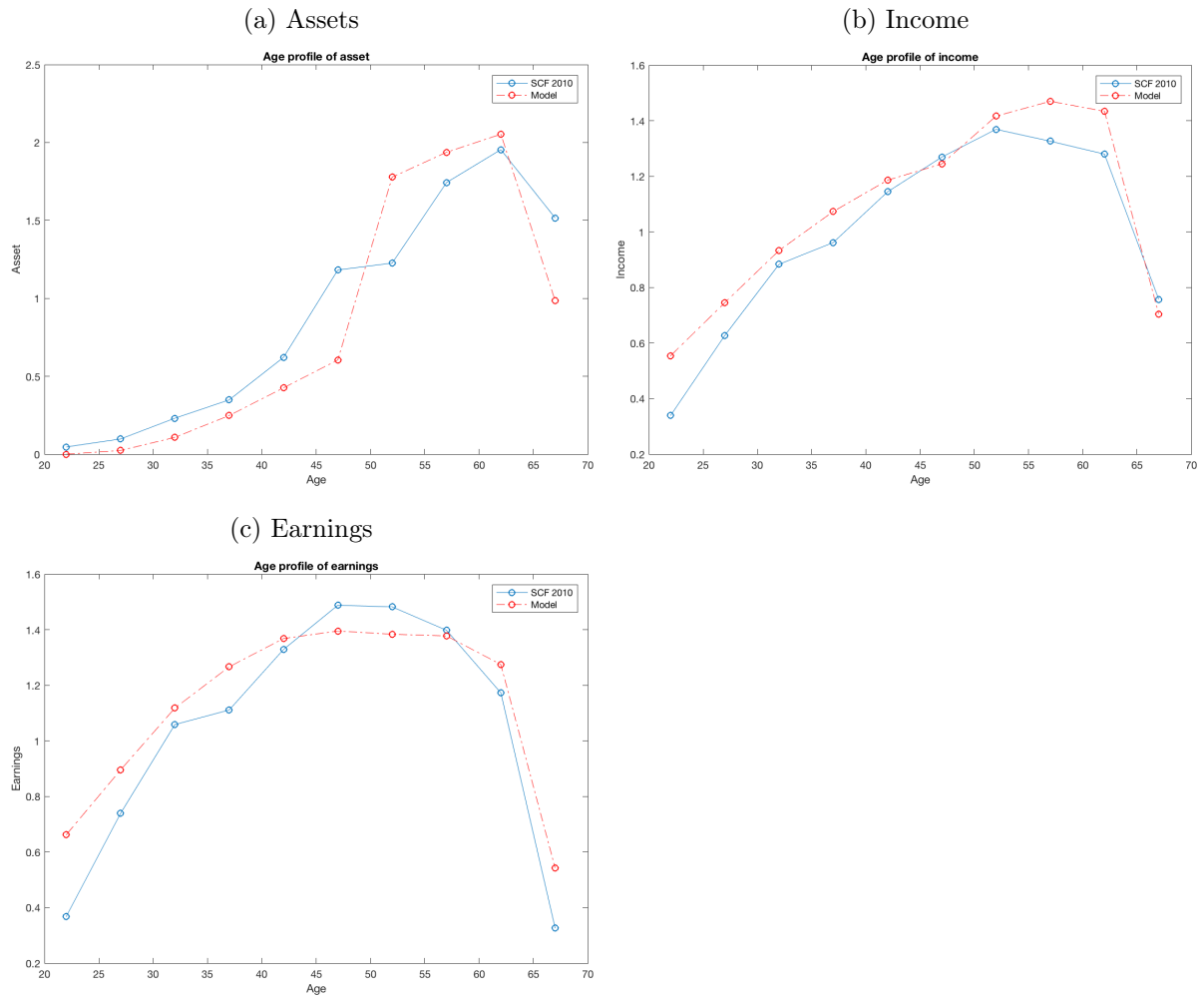
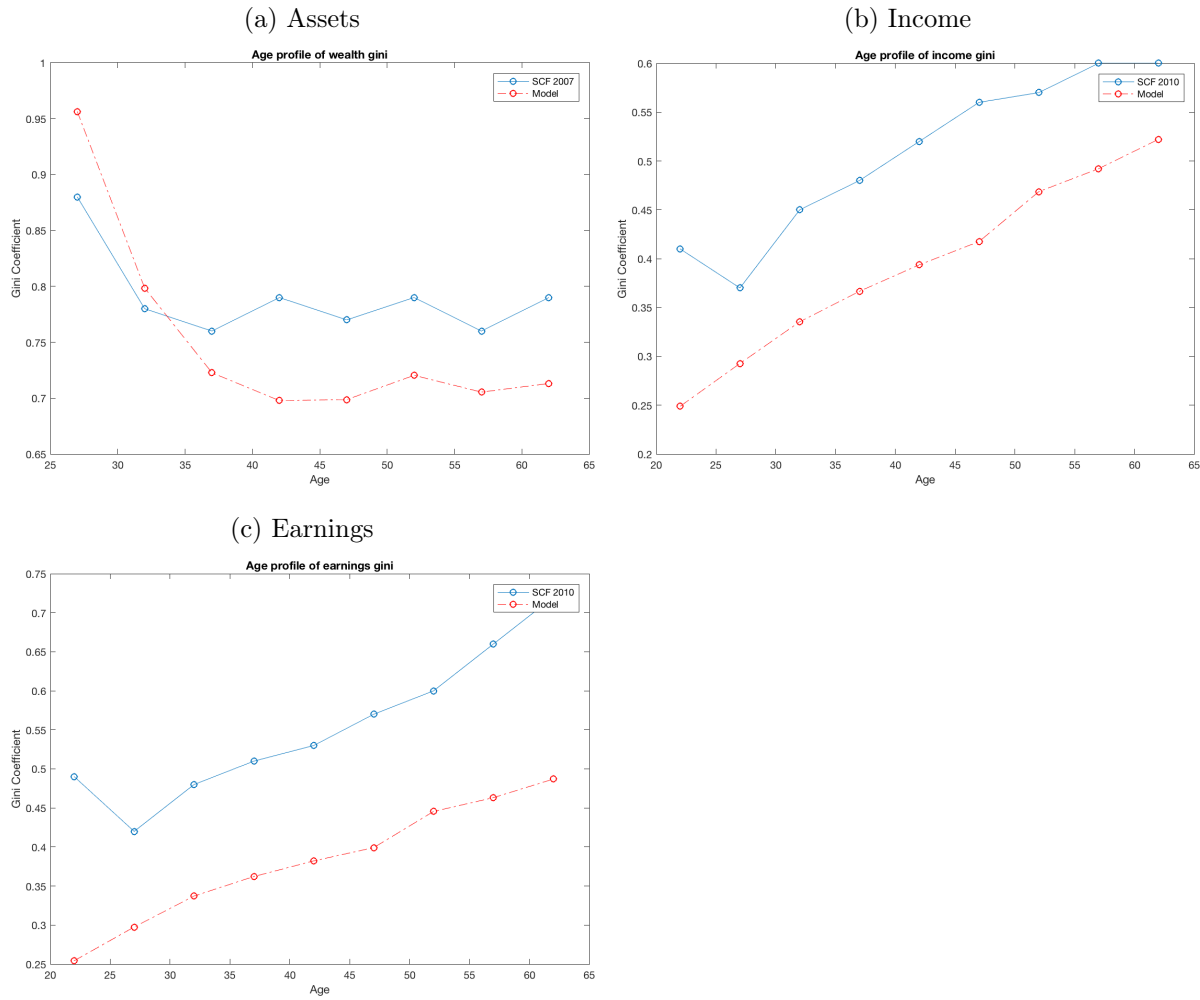


Figure 2: Gini Coefficients for Earnings, Income and Assets Inequality over the Life-Cycle



asset accumulation becomes more prevalent among households. This reduces the Gini coefficient in the first part of the life-cycle. 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 US. In particular, we conduct a decomposition exercise where we eliminate each factor individually from the model and study the implied wealth

Table 15: Determinants of Wealth Concentration

<i>Wealth Share</i>	Top Percentile						Gini
	0.01%	0.1%	0.5%	1%	5%	10%	
Benchmark	0.029	0.117	0.267	0.368	0.590	0.693	0.823
No top earners	0.018	0.073	0.204	0.304	0.537	0.652	0.797
No het. return	0.013	0.085	0.220	0.317	0.539	0.647	0.798
No bequest	0.011	0.059	0.169	0.248	0.455	0.580	0.752
Take away all	0.004	0.036	0.137	0.212	0.413	0.539	0.725
<i>Income Share</i>	0.01%	0.1%	0.5%	1%	5%	10%	Gini
	0.01%	0.1%	0.5%	1%	5%	10%	
Benchmark	0.011	0.047	0.129	0.172	0.281	0.367	0.456
No top earners	0.006	0.034	0.114	0.147	0.255	0.335	0.445
No het. return	0.008	0.030	0.111	0.153	0.266	0.353	0.447
No bequest	0.007	0.034	0.111	0.146	0.257	0.347	0.447
Take away all	0.002	0.024	0.095	0.122	0.225	0.307	0.428

distribution with the benchmark calibration. This allows us to gauge the contribution of each factor to wealth concentration. Then, we recalibrate the model in the absence of each factor to replicate the observed wealth distribution in the data, and study its implications for the joint distribution of earnings, income and wealth. The latter helps highlight the main identification mechanisms in our calibration.

Table 15 shows the results from the 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. When the very high earning states are ignored, both income and wealth concentration falls dramatically. The drop is sharpest for the top 1% and the 0.5% shares. The gini coefficient drops slightly from 0.82 to 0.8. That the Gini coefficient does not drop as much as top wealth shares reflects the significance of households without any assets for the calculation of the Gini.

When the heterogeneity in the rate of return on assets is eliminated, a drop of similar magnitude is observed in the top wealth shares. The sharpest drops are observed for the top 0.1% and 0.01% shares. This indicates the relevance of stochastic capital income risk in generating the right-tail of the income distribution.

Bequests are considerably important for wealth concentration as they allow for substantial wealth accumulation across generations of a dynasty. Banning households from leaving bequests

Table 16: Key Identifying Moments

	corr(e,w)	corr(y,w)	k share for 1pct
Benchmark	0.21	0.58	0.43
w/o ret het.	0.29	0.54	0.35
w/o top earners	0.14	0.62	0.47

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.

cuts the top wealth shares considerably. The Gini coefficient drops to 0.75 from its benchmark value of 0.82.

Next, we recalibrate versions of the model without the key determinants of wealth concentration. First, we eliminate rate of return heterogeneity by setting $r_H = r_L = r$, and adjust the top earnings levels in order to match the wealth concentration observed in the data. Next, we eliminate the top earnings states from the model by setting them equal to the top ordinary earnings level, and re-calibrate the rate of return on assets and the bequest parameter to match the wealth concentration. Table 16 reports the correlations of income and earnings with wealth as well as the share of income from labor for the top 1% of the income distribution in each case.

Next, we shut down the highest earnings state and raise the dispersion of the stochastic rate of return process, and adjust the bequest motive to match the observed wealth concentration. Increasing the dispersion the rates of return leads to a significant drop in the link between in earnings and wealth. The correlation coefficient in this economy is two thirds of the benchmark model. This implies that earnings are crucial for the observed wealth concentration in US. The correlation between wealth and income increases by about 13 percent. This increase remains limited relative to 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.

When return heterogeneity is eliminated and the top earnings states are elevated to match the wealth concentration, opposite patterns are observed. Wealth-earnings correlation increases and the income-earnings correlation decreases. Labor's share of income among the top 1% income earners increases.

7 Implications for Top Income Tax Elasticities

8 Conclusion

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Appendix: Additional Tables and Figures

Average tax rates by income group in the benchmark economy

	Corporate tax			Income tax			
	1%	99%	R/Y	1%	99%	ATY1-ATY99	R/Y
Data	5.1%	1.9%	1.9%	26.73%	19.91%	6.82%	23%
Model	5.92%	0%	0.62%	25.11%	18.12%	6.99%	12.38%

Note: Income tax R/Y should not be 23%

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

Life cycle profiles

	<25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65	66+
Wealth (data)	0.0466	0.0977	0.2309	0.3485	0.6213	1.1823	1.2262	1.7432	1.9543	1.5157
Model	0.0	0.0288	0.1392	0.3020	0.4901	0.6712	1.7769	1.9148	2.0029	0.9135
Income (data)	0.3393	0.6274	0.8833	0.9619	1.1440	1.2690	1.3690	1.3262	1.2798	0.7571
Model	0.5570	0.7545	0.9590	1.1033	1.2109	1.2652	1.4074	1.4578	1.4163	0.6894
Earnings (data)	0.3679	0.7387	1.0586	1.1111	1.3288	1.4880	1.4820	1.3979	1.1727	0.3258
Model	0.6562	0.8954	1.1348	1.2826	1.3736	1.3936	1.3757	1.3676	1.2626	0.5476

Gini Coefficient by age groups (Rio Rull & Kuhn 2016)

	<25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65
Wealth Gini (2007SCF)		0.88	0.78	0.76	0.79	0.77	0.79	0.76	0.79
Model		0.9496	0.6954	0.6513	0.6437	0.6562	0.6865	0.6774	0.6908
Income Gini (2010SCF)	0.41	0.37	0.45	0.48	0.52	0.56	0.57	0.60	0.60
Model	0.2531	0.2985	0.3368	0.3675	0.3932	0.4171	0.4609	0.4864	0.5172
Earnings Gini (2010SCF)	0.49	0.42	0.48	0.51	0.53	0.57	0.60	0.66	0.72
Model	0.2600	0.3045	0.3368	0.3675	0.3932	0.4171	0.4609	0.4864	0.5172

Pareto Distributions

