Belief Heterogeneity and the Income-Wealth Relationship*

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Abstract

Overlapping generations models with uninsurable idiosyncratic income risk struggle to match the right skew observed in the U.S. wealth distribution, and the weak correlation between income and wealth inequality we document in a cross-section of 28 countries. We argue that a realistic deviation from full information rational expectations may help standard models match these features of the data. A simple model in which agents have heterogeneous beliefs about personal employment probabilities, and learn from personal employment experience, can generate significant right skew in the wealth distribution, and a range of different wealth distributions for a given income distribution.

Keywords: Learning, Life-cycle Model, Heterogeneous Information, Wealth Inequality.

JEL codes: E10, E21, E71.

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1 Introduction

It has been established empirically that the wealth distribution displays significantly more right skew than the distribution of income in the United States and around the world.[1] Further, it has been shown that there is a great deal of heterogeneity in the relationship between income and wealth inequality across countries.[2] Both features of the data are difficult to replicate using standard life-cycle models of the wealth distribution, which postulate uninsurable idiosyncratic income risk as a root cause of wealth heterogeneity. Specifically, standard life-cycle models fail to match key features of the US wealth distribution including the thick right tail (Huggett (1996)), and they further imply a strongly positive relationship between income and wealth inequality in contrast to the weak income-wealth relationship observed in the data (Benhabib et al. (2017)). These models typically assume full information rational expectations (FIRE), despite evidence of heterogeneous, non-rational beliefs.

This paper makes two contributions to the conversation on modeling the income-wealth relationship. First, we provide an updated estimate of the relationship between income and wealth inequality using a much larger cross-section of countries than previous work, such as Benhabib et al. (2017). Our analysis confirms earlier findings that the earnings Gini coefficient is **not** a statistically significant predictor of the wealth Gini coefficient. Second, we embed heterogeneous beliefs about about personal employment probabilities into an otherwise standard life-cycle model economy, and illustrate that simple deviations from full information rational expectations (FIRE) generate a far greater degree of wealth skew than traditional FIRE models, and can generate a wide range of wealth distributions for a given income distribution. Thus, belief heterogeneity may help rationalize right skew in the wealth distribution and the poor predictive power of income inequality for wealth inequality.

Sections 2 and 3 discuss evidence of heterogeneous employment beliefs, and the income-wealth relationship for 28 countries. Section 4 develops a simple model of belief heterogeneity, and section 5 studies model-implied wealth distributions for a given income distribution.

2 Evidence of Heterogeneous Employment Beliefs

Our view that labor market expectations are diverse and impacted by personal experience is supported by a growing literature. A 2019 College Pulse survey asked 7,000 students in the U.S. how much money they expect to make after graduation, and found their median salary expectation exceeded the actual median salary for graduates with 0-5 years experience by \$12,000.[3] Over-optimism is not unique to this survey: Jerrim (2015) shows that college-aged individuals overestimate life-time income by 40%; Alesina et al. (2018) provide evidence that Americans predict unreasonably high upward mobility; Mueller et al. (2018) document over-optimism among unemployed workers with respect to their re-employment beliefs. There is

[1]See Vermulen, 2016; Piketty 2014 for a discussion of the empirical income-wealth relationship and DeNardi and Fella, 2017, for a survey of the literature aimed at generating realistic degrees of wealth inequality in heterogeneous agent life-cycle economies

[2]See Benhabib et al., 2017; Jannti et al.; 2008

[3]See Mike Brown's LendEDU report "Expectations vs. Reality: Early Career Salaries."

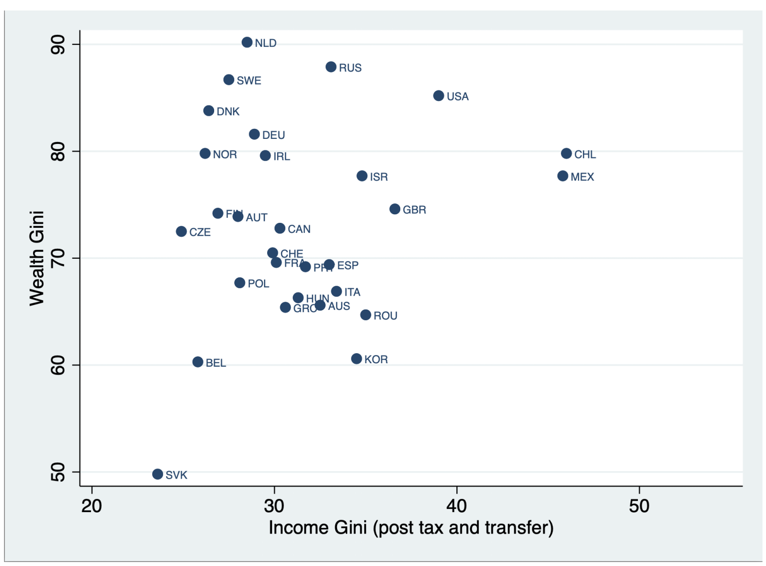
also compelling evidence of over-pessimism: Tortorice (2012) shows that Michigan Survey of Consumers respondents underestimate their re-employment probability after recessions. Rozyspal and Schlafmann (2019) corroborate this finding, noting that individuals are more likely to be pessimistic than optimistic when forecasting their personal income trajectory.

Finally, there is evidence that people's beliefs about employment prospects are always diffuse and highly dependent on individual employment experiences. Guvenen (2007) finds an individual's uncertainty about their personal income growth is slowly resolved over the life-cycle, in part because idiosyncratic income shocks are infrequent and not very persistent. Ellison and Macauley (2019) use Survey of Consumer Expectations (SCE) data to outline a great deal of dispersion in household expectations regarding the probability of re-employment following a theoretical job loss. This high degree of belief dispersion persists even after controlling for individual income, age, education, race, and a host of other demographic variables. This paper offers a model capable of characterizing how optimism, pessimism, and heterogeneity of beliefs regarding idiosyncratic earnings manifests in economy wide outcomes.

3 The Income-Wealth Relationship

Benhabib et al. (2017) provide evidence that the earnings Gini coefficient is a poor predictor of the wealth Gini coefficient using data from 9 countries. Here we provide an updated account of this relationship utilizing the 2019 Credit Suisse Global Wealth Report, which harmonizes wealth data for a larger number of countries. We combine all wealth data labeled as satisfactory or above by Credit Suisse with OECD data (2021) on post tax and transfer income inequality to generate a dataset of 28 countries[4].

Figure 1: Income and Wealth Gini



[4]As many wealth surveys (like the US Survey of Consumer Finances) are not conducted annually, we match the most recent OECD income data (2017-2019) with the wealth data reported by Credit Suisse spanning the same time frame.

The Benhabib et al. result is preserved in our much larger sample. The slope coefficient associated with Figure 1 is just .34 with a standard error of .33, and the R^2 of this regression is .04. We conclude that income inequality is not an adequate predictor of wealth inequality.

4 The Model

Here we outline a model with heterogeneous beliefs about personal employment. The modeling environment is a simplified version of the standard multi-period overlapping generations model first introduced in Huggett (1996). In each period, a continuum of households are born with no assets, a non-stochastic lifespan of length J, and no bequest motives. It follows that a generation of households also dies in each period after consuming all their resources at age J. There is no population growth. Labor is supplied inelastically for the first $j_R < J$ periods after which point households retire. Household, i, of age ($j \in \{1, ..., J\}$) chooses their savings allocation ($\{a^{j,i}_{t+j-1}\}^{J-1}_{j=1}$) by solving a standard intertemporal optimization problem:

$$\max_{\{a^{j,i}_{t+j-1}\}^{J-1}_{j=1}} \hat{E}_t \sum_{j=1}^{J} \beta^{j-1} u(c^{j,i}_{t+j-1}) \tag{1}$$

$$\text{s.t.} \qquad c^{j,i}_{t+j-1} + a^{j,i}_{t+j-1} \leq R_{t+j-1} a^{j-1,i}_{t+j-2} + \epsilon(s^{j,i}_{t+j-1}) h(j) w_{t+j-1} \tag{2}$$

where $u(c) = (c^{1-\sigma} - 1)/(1-\sigma)$, $\hat{E}_t$ denotes (potentially) non-rational expectations formed at t, R_{t+j-1} and w_{t+j-1} are the economy wide return on savings and labor, respectively, $h(j)$ is the hump-shaped, deterministic age-earnings profile[5], and $s^{j,i}_{t+j-1}$ is a two-state persistent exogenous Markov process governing the idiosyncratic employment risk faced by optimizing households. The transition out of state $s \in \{L, H\}$ such that $0 \leq \epsilon(L) < \epsilon(H) = 1$ is governed by the Markov transition probabilities $P_L = Pr(\epsilon' = \epsilon(L)|\epsilon = \epsilon(L))$ and $P_H = Pr(\epsilon' = \epsilon(H)|\epsilon = \epsilon(H))$. The high employment state, $\epsilon(H)$, corresponds to full time employment and the low employment state, $\epsilon(L)$, corresponds to unemployment.

We introduce heterogeneous beliefs as follows. In each period, ϕ proportion of newborn agents are endowed with knowledge of P_H and P_L. These **informed** (I) agents form expectations using the true employment probabilities when solving (1). Of the remaining $1 - \phi$ proportion of agents, λ proportion are **pessimists** (P) (i.e. born with initial employment transition probability beliefs (P^P_H,P^P_L) such that $P^P_H < P_H$ and $P^P_L > P_L$), and $1 - \lambda$ proportion are **optimists** (O) (i.e. born with initial beliefs (P^O_H,P^O_L) such that $P^O_H > P_H$ and $P^O_L < P_L$). Intuitively, pessimists underestimate the frequency and duration of the high employment state when forming expectations to solve (1), which leads pessimists to over-accumulate assets relative to other agents over the life-cycle. For analogous reasons, optimists under-accumulate wealth. Thus, non-rational employment expectations directly impact the aggregate wealth distribution. Finally, pessimists and optimists are assumed to update their beliefs about employment transition probabilities recursively using simple sta-

[5] $h(j)$ replicates the age-earnings profile in Huggett (1996).

tistical tools and their own employment data, in the spirit of Evans and Honkapohja (2001).[6] Importantly, the learning mechanism enables agents to learn from personal employment experience but does not cause belief heterogeneity to vanish, since agents have finite lifespans and do not share information with other households within or across generations. We note that the household-side of the economy collapses to an entirely standard FIRE framework when $\phi = 1$.

All other features of the economy are standard: output is determined by a Cobb-Douglas production function with labor and capital as inputs; factor prices are determined competitively, and labor, goods, and asset markets clear in each period. See the online appendix for more details.

5 Calibration and Results

In this section, we provide an overview of the model calibration and present results from several calibration exercises in which we vary the proportion of agents endowed with optimistic preferences.

5.1 Calibration

Now we calibrate our simple model and study the model-implied aggregate wealth distribution. Throughout this section, we hold fixed β, σ, firm and labor market parameters (i.e. capital share, α, depreciation rate, δ, and P_L, P_H, $\epsilon(H)$, $\epsilon(L)$), learning gain parameters (γ_H and γ_L), initial beliefs (P_L^O, P_H^O , P_L^P , P_H^P), and demographic parameters (J, j_R) (see Table 1 for details). Note that by fixing these parameters, we are holding the income distribution constant throughout this section.

Our choice of $\alpha, \beta, \sigma, \gamma_H$ and γ_L are standard in the literature. The transition probabilities (P_L and P_H) are calibrated to match estimated employment transition probabilities from PSID data in Ashman and Neumuller (2019).[7] Payoffs, $\epsilon(H)$ and $\epsilon(L)$, were selected so that the high employment state corresponds to receiving the economy-wide wage and the low-employment state provides a non-zero payoff so that age 1 agents are guaranteed positive consumption. Our calibration of the terms governing optimism and pessimism (P_L^O, P_H^O, P_L^P, and P_H^P) were chosen so that optimists believe they will always be employed until experience causes them to update beliefs and pessimists think there is a 50-50 probability of unemployment next period regardless of their current employment state.[8]

[6] Agents update beliefs about the transition probabilities using a simple recursive specification with a constant gain parameter and their own personal employment data given initial beliefs about the transition probabilities. See the online appendix for more on the learning specification and other modeling details. We follow Kreps' (1998) anticipated utility approach and assume that agents do not account for the fact that estimates are time-varying when solving (1).

[7] Ashman and Neumuller provide estimates of the semi-annual transition probabilities into and out of unemployment broken down by race, education, and family structure. Their estimates indicate that an annualized $P_H \in (.79, .995)$ and an annualized $P_L \in (.09, .50)$.

[8] We selected a 50-50 split for pessimists' beliefs in light of recent research by Enke and Graeber (2019) which argues that agents faced with uncertain binary environments are likely to gravitate towards 50-50 probabilities as their default. Alternative calibrations result in qualitatively similar wealth distributions.

Table 1: Calibration

Parameter	Value	Interpretation
β	0.96	Discount Rate
σ	2.0	IES
α	0.33	Capital Share
δ	0.025	Depreciation rate of capital
P_L	0.3	$Pr(\epsilon' = \epsilon(L)\|\epsilon = \epsilon(L))$
P_H	0.9	$Pr(\epsilon' = \epsilon(H)\|\epsilon = \epsilon(H))$
P_L^O	0	Optimist Initial Belief: $Pr(\epsilon' = \epsilon(L)\|\epsilon = \epsilon(L))$
P_H^O	1	Optimist Initial Belief: $Pr(\epsilon' = \epsilon(H)\|\epsilon = \epsilon(H))$
P_L^P	.5	Pessimist Initial Belief: $Pr(\epsilon' = \epsilon(L)\|\epsilon = \epsilon(L))$
P_H^P	.5	Pessimist Initial Belief: $Pr(\epsilon' = \epsilon(H)\|\epsilon = \epsilon(H))$
$\epsilon(H)$	1	Payoff if employed
$\epsilon(L)$	0.1	Payoff if unemployed
γ_H	0.04	Gain parameter learning on high state
γ_L	0.04	Gain parameter learning on low state
J	62	Length of agent's life
j_R	45	Retirement age

5.2 Results

Table 2 and Figure 2 highlight our results from several model calibrations in which we vary the proportion of agents with pessimistic preferences ($\lambda \in [0, 1]$) while fixing the fraction of informed agents ($\phi = 0$). Results are compared to a benchmark economy comprised of FIRE agents ($\phi = 1$). Table 2 displays the Gini coefficient on wealth (Gini_W) and income (Gini_I) along with the market clearing interest rate (r) for each calibration.

Table 2: Wealth Statistics in Model Economies

	FIRE	$\lambda = 0$	$\lambda = .10$	$\lambda = .25$	$\lambda = .50$	$\lambda = .75$	$\lambda = .90$	$\lambda = 1$
Gini_W	40.9	45.0	44.9	44.4	42.6	40	38.2	36.9
Gini_I	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
r	2.8	3.6	3.3	3	2.5	2.1	1.9	1.8

It is clear that when the economy is comprised of many optimists ($\lambda < .5$), the low savings propensity of optimistic households bids up the market interest rate and leads to greater inequality than a model comprised of FIRE or a majority of pessimistic agents. This increased inequality occurs as many optimistic agents hold low or 0 wealth while the high market interest rate provides pessimistic agents and optimists who have experienced negative income shocks (and thus shed their optimism) with high returns relative to a model comprised of rational agents.

Our results indicate that belief diffusion may be an important mechanism for rationalizing the weak empirical relationship between income and wealth inequality outlined in Section 3. Each model economy has an identical income process (Gini_I=25), however the wealth Gini coefficient ranges from 10% higher than Gini_W in the FIRE economy to 9.7% lower, simply by varying the proportion of agents with initial mis perceptions of the earnings process. Although the values of Gini_W fall well below the value of the wealth Gini in U.S. data (≈ 80), this is primarily a function of the low degree of income inequality we feed into our model.

As our focus is outlining the impact of belief heterogeneity on economy-wide outcomes and not matching specific moments of the wealth distribution, we chose a simpler 2-state earnings process than what is typically fed into life-cycle models. This 2-state earnings process provides a clear way of assigning optimism and pessimism with respect to perceived employment probabilities (see Section 4) whereas a more robust earnings process would require a less intuitive learning environment. Future work will be aimed at directly calibrating the belief distribution in the model economy using Survey of Consumer Expectation (SCE) data in modeling environment with much greater skew in the imposed income distribution.

Figure 2: Wealth Distribution Across Modeling Environments

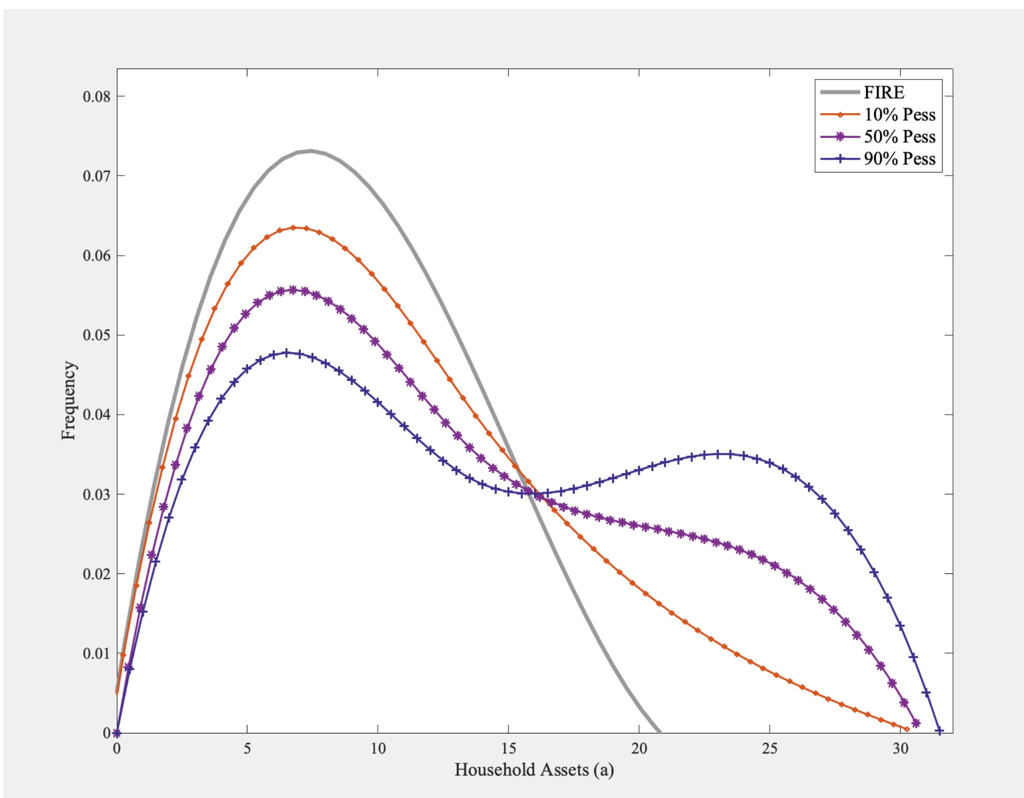


Figure 2 provides evidence of increased right skew in the wealth distribution when agents hold biased beliefs. We plot the wealth distribution in the FIRE economy as well as the wealth distribution when $\lambda = .1, .5,$ and .9, respectively. When $\lambda = .1$, meaning there are many optimists and a few pessimists, the tail behavior of the wealth distribution bares little resemblance to the tail behavior of the FIRE model economy. Instead, a small number of agents amass wealth well above the majority of households in their economy and the FIRE maximum. As λ increases to .5, the tail of the wealth distribution becomes thicker and the left mass flatter as more pessimistic agents with a high savings propensity accumulate high wealth. However, as λ nears 1 and the vast majority of agents are pessimistic and the return on savings is low, the wealth distribution looks nearly uniform and the tail behavior is fairly indistinguishable from the FIRE economy.

We conclude that belief heterogeneity may be a strong predictor of the tail behavior of the wealth distribution. As there is considerable interest surrounding matching the top-end of the wealth distribution in calibrated life-cycle models, we believe this mechanism merits further exploration.

6 Conclusion and Future Work

We show that a modest, realistic deviation from full information rational expectations can dramatically reshape the economy-wide wealth distribution. Our mechanism generates a more realistic degree of skewness in the aggregate wealth distribution than a standard model with FIRE. Further, heterogeneous beliefs about personal employment risk may help rationalize our finding that the income Gini coefficient is a poor predictor of the wealth Gini coefficient in 28 countries. In our model, the same income process with a Gini coefficient of 25.0 is capable of generating a wealth distribution with Gini coefficients between 36.9 and 45.0.

Many avenues for future research remain. First, these beliefs could be calibrated utilizing the Survey of Consumer Expectations and embedded in a quantitative life-cycle model in order to study whether belief heterogeneity accounts for the high degree of inequality observed in US wealth data. Second, we hope to extend our model of idiosyncratic learning to a model of learning within networks. In such an environment, agents will utilize personal information as well as information from network members to formulate forecasts.

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