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A Comment on “Wealth Inequality and Endogenous Growth” by Byoungchan Lee*

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Abstract

How does wealth inequality affect economic growth? Byoungchan Lee answers this question by developing a heterogeneous-agent model and augmenting it with endogenous firm innovation. The novel channel is that rising wealth concentration reduces aggregate demand, which gives firms a disincentive to spend on R&D and therefore leads to slower productivity growth. In this discussion, we first explain the difference in calibration strategy between Lee's approach and the common approach in the literature, and then discuss its quantitative implications for the effect of rising inequality on aggregate consumption.

Keywords: heterogeneous-agent model, wealth inequality, aggregate consumption

JEL classification: D31, D52, E21

*The views stated herein are those of the authors and are not necessarily those of the Federal Reserve Bank of Cleveland or the Board of Governors of the Federal Reserve System.

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1 Overview

In recent decades, many advanced economies have been experiencing both a slowdown in economic growth and a rise in income and wealth inequality. To study the relationship between these two trends, Byoungchan Lee develops and quantifies a novel channel through which rising wealth inequality can reduce productivity growth rates.

Lee first provides cross-country evidence showing the empirical trends of rising inequality, decreasing demand intensity,[1] and decreasing R&D intensity in recent decades. To explain the joint dynamics of these factors, he develops an analytically tractable heterogeneous-agent model and augments it with endogenous growth. On the demand side, because rich households save more, an increase in wealth concentration yields a decline in demand intensity. On the supply side, lower demand intensity leads to smaller market size, in which case profit-maximizing firms find it less profitable to spend on R&D. Less R&D expenditure then leads to slower economic growth. The calibrated model suggests that rising wealth inequality significantly reduces productivity growth and leads to large welfare costs in the US from the early 1980s to the late 2010s.

Our discussion focuses on the robustness of the paper's findings to the specification of the demand side of the model. After summarizing the relationship between wealth inequality and consumption intensity, we explore three extensions of Lee's model: including a persistent component in the income process, disciplining the changes in income risks, and allowing for individual-state-dependent consumption function parameters.

2 Key Mechanism of the Paper

In Lee (2022), a rise in wealth inequality drives a decline in the rate of economic growth by affecting consumption intensity. We summarize the key mechanism as follows. First, the

[1] Demand intensity is defined as the ratio of aggregate consumption to aggregate wealth. In Lee (2022), demand intensity is used interchangeably with consumption intensity, but both are different from aggregate consumption. We will further explain this difference in later sections.

consumption function derived in Lee (2022) (Proposition 1) is concave in wealth inclusive of income, given by

$$c_t = \zeta(x_t + \phi)^{\xi}, \qquad 0 < \xi < 1 \tag{1}$$

where c_t denotes consumption and x_t denotes wealth inclusive of income. ζ, ξ, and ϕ denote the scale, shape, and borrowing limit, respectively.[2] Equation (1) implies that rich households have a lower consumption to wealth ratio, and therefore a rise in wealth concentration reduces aggregate consumption intensity.

Lee makes a novel contribution by showing an analytically tractable relationship between wealth distribution and aggregate demand intensity, which is given by

$$s_C = \frac{\zeta exp\left(\xi\mu_a\right)}{1-\frac{1}{2}\xi^2\sigma_a^2} / \left[\frac{exp\left(\mu_a\right)}{1-\frac{1}{2}\sigma_a^2} - \phi\right]. \tag{2}$$

Equation (2) shows that demand intensity is governed by three consumption function parameters (ζ, ξ, and ϕ) and two wealth distribution parameters (μ_a and σ_a). Therefore, how demand intensity changes with wealth distribution crucially depends on the value of the consumption function parameters, especially the concavity of the consumption function, ξ. The value of ξ critically determines the impact of wealth distribution on productivity growth.

To further show the quantitative implications of ξ, we plot the relationship between demand intensity and wealth inequality under different ξ according to Equation (2). Figure 1 shows that for the same increase in wealth inequality, measured by σ_a, the more concave the consumption function is (the lower the value of ξ is), the larger the decrease in consumption intensity.

[2] In Lee (2022), the borrowing limit is denoted by η. We use ϕ instead of η to make this function consistent with our model setup in Section 3.

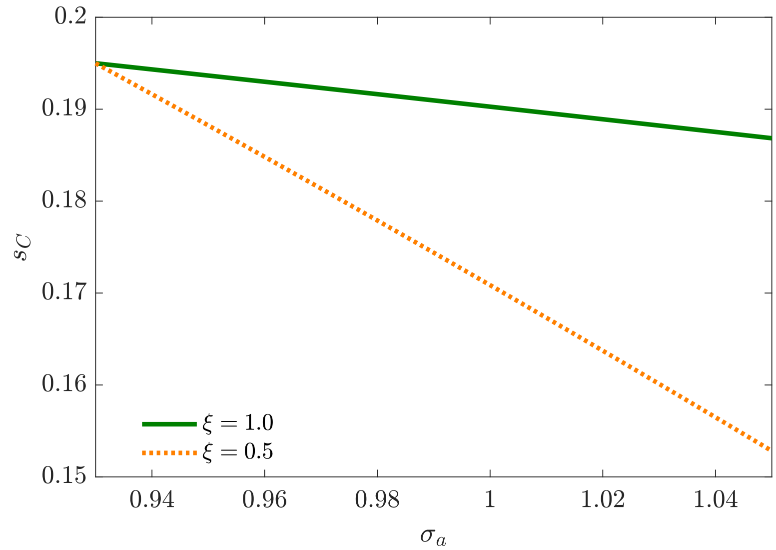

Figure 1: The Relationship Between Demand Intensity and Wealth Inequality

3 Discussion

To guide our discussion, we first sketch out the original Aiyagari (1994) model, which helps explain the methodological difference between Lee's approach and the standard approach in the literature in calibration. We then discuss three different ways in which this difference may change the quantitative effect of rising wealth inequality on aggregate consumption.

Model. The economy consists of a continuum of households that have labor income and are subject to idiosyncratic earnings shocks. Their labor endowment, y_t, is the sum of two orthogonal components, given by

$$\log y_t = z_t + \epsilon_t.$$

z_t^i is the persistent component of labor earnings risk following an AR(1) process,

$$z_t = \rho z_{t-1} + \eta_t,$$

where $\eta_t \overset{iid}{\sim} \mathrm{N}(0, \sigma_\eta)$. ϵ_t is the transitory component of labor earnings risk with $\epsilon_t \overset{iid}{\sim} \mathrm{N}(0, \sigma_\epsilon)$.

Households maximize their expected lifetime utilities by making optimal consumption c_t and savings b_{t+1} decisions. They can borrow up to a limit of ϕ. The recursive formulation of the household's problem is given by

$$v(b_t, z_t, \epsilon_t) = \max_{c_t, b_{t+1}} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}\left[v(b_{t+1}, z_{t+1}, \epsilon_{t+1}) \right] \right\}$$

, subject to

$$c_t + b_{t+1} = (1 + r_t) b_t + w_t y_t(z_t, \epsilon_t),$$

$$c_t \geq 0, \quad b_{t+1} \geq -\phi,$$

where w_t is the wage rate, r_t is the interest rate, and σ is the risk aversion parameter. Wealth inclusive of income is defined as $x_t = (1 + r_t) b_t + w_t y_t(z_t, \epsilon_t)$, consistent with Lee (2022).

There is a representative firm that has a constant-returns-to-scale production technology, hires labor at the wage rate of w_t and rents capital at the cost of $r_t + \delta$, where δ is the depreciation rate. The firm's problem is given by

$$\max_{K_t, L_t} \left\{ K_t^{\alpha} L_t^{1-\alpha} - (r_t + \delta) K_t - w_t L_t \right\}$$

where K_t and L_t are aggregate capital and labor demand, respectively, and α is the capital share in the production function.

Since the definition of a recursive competitive equilibrium for this economy is standard, we omit it in this discussion.

Calibration. The common way in the literature to calibrate this model is to estimate the process of the exogenous variables, which in this case is the income process, and compare the model-predicted endogenous variables, which in this case are wealth distribution σ_a and the consumption concavity parameter, ξ, with their empirical counterparts in the data.

Following this standard approach, we feed in an estimated income process that is char-

Table 1: Model Parameters

Parameter		Value
(A) Assigned parameter		
Capital share	α	0.36
Risk aversion	σ	2.00
Persistence of shocks	ρ	0.99
SD of persistent earnings shocks	σ_η	0.12
SD of transitory earnings shocks	σ_ϵ	0.25
(B) Calibrated parameter		
Discount rate	β	0.94
Depreciation rate	δ	0.08
Borrowing limit	ϕ	0.17

acterized by the coefficients ρ, σ_η, and σ_ϵ (Guvenen (2009)). We calibrate other model parameters to match other crucial features of the US economy. First, we set the capital share in the production function $\alpha = 0.36$ and the risk aversion $\sigma = 2.0$, both of which are standard values in the literature. Then, we internally calibrate three parameters to minimize the distance between the model and the data. The discount factor, β, is chosen to match a real interest rate of 4 percent. The annual depreciation rate, δ, is set to match a capital-output ratio of 3.0. The borrowing limit, ϕ, is calibrated to target the fraction of households with negative net worth of 9.7 percent (according to the 2007 Survey of Consumer Finances). All parameter values are reported in Table 1.

We find that this calibrated model is capable of generating a realistic income and wealth distribution, as reflected by the two non-targeted moments, including the standard deviation of log household earnings (0.82 in the model and 0.81 in the data)[3] and the top 20 percent share of wealth inclusive of income (0.67 in our model and 0.67 in the data reported in Lee (2022)). Moreover, to compare the predictions of this model with those in Lee (2022), we calculate the model-generated consumption concavity parameter, ξ. To do so, we compute

[3] We calculate standard deviation of log earnings by taking the square root of the variance series for the earnings of individuals in firms with more than 20 employees reported in Song et al. (2019). In Table 2, we use the average from 1978 to 1980 for the initial steady state calibration (0.82). In table 3, we use the average from 2011 to 2013 for the final steady state calibration (0.92). Data source: `https://www.fatihguvenen.com/s/fui_graphdata_20160928.xls`.

Table 2: Targeted and Non-targeted Model Statistics

	Model	Data
(A) Targeted moments		
Real interest rate	4.0	4.0
Capital to output ratio	3.0	3.0
Households with negative asset %	9.7	9.7
(B) Non-targeted moments		
SD of log earnings	0.82	0.81
Top 20% share wealth inclusive of income	0.67	0.67
Regression coefficient: ξ	0.58	0.50

the stationary equilibrium of the calibrated model by simulating a large number of households for a long period of time. Then, we estimate ξ by doing an OLS regression of model-simulated log consumption on model-simulated log wealth inclusive of income for all households. We find that the model-predicted regression coefficient ξ is reasonably close to the data (0.58 in our model and 0.50 in the data reported in Lee (2022)).

A Methodological Difference. In comparison, Lee takes the opposite approach. He estimates the endogenous variables - wealth distribution (σ_a) and the consumption function parameter (ξ) - at the initial steady state from the data and uses the optimality condition derived from the model to reverse engineer the parameters characterizing the income process (Section 4.3 in Lee (2022)). Under the same logic, Lee measures the changes in wealth distribution from the data on the transition path and uses this to back out the changes in the income shock process. In what follows we discuss how this difference affects the quantitative results of the model.

3.1 The Assumption on the Structure of Income Shocks

Lee assumes that there is no persistent component in the income shocks. Although this assumption might be necessary for a tractability purpose, we question the validity of this assumption by showing that the value of ξ is sensitive to the persistence of shocks. In

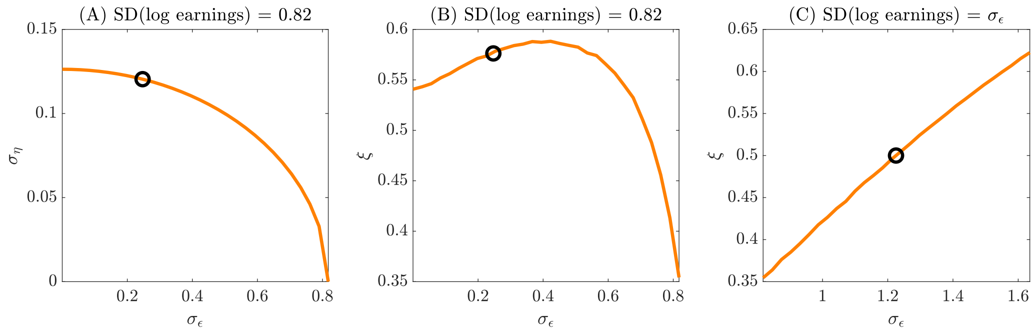

Figure 2: Standard Deviation of Transitory Shocks and the Simulated ξ

In Panel (A), the black circle indicates the values of σ_ϵ and σ_η under our calibration. In Panel (B), the black circle shows the model-implied value of ξ under our calibration. In Panel (C), the black circle indicates the value of σ_ϵ when ξ is targeted at 0.5 and the earnings shocks have only transitory components.

addition, Lee assumes that the transitory shocks follow a Laplacian distribution, and in a companion paper (Lee (2021)), Lee shows that a Laplacian distribution better captures the shape of the earnings distribution than a normal distribution does. However, by removing the persistent shocks and estimating the shock parameters to fit the shape of the earnings distribution, Lee implicitly assumes that the earnings distribution is equivalent to the shocks distribution, which may not be a realistic characterization of the actual income risk faced by households.

To show how ξ varies with the persistence of income shocks, we perform the following numerical exercises: First, we fix the standard deviation of log labor earnings at 0.82, which is consistent with the estimation in Song et al. (2019). Next, we also fix ρ at 0.99 and vary the value of σ_ϵ from 0 to 0.82. We adjust the σ_η accordingly to account for the rest of the income dispersion. By doing so, we change the role played by the transitory component of the income shocks to account for 0 percent to 100 percent of the dispersion in log labor earnings. For each combination of $(\sigma_\epsilon, \sigma_\eta)$, we re-calibrate the discount factor β to ensure that the capital market clears, adjust the wage rate w_t to ensure that the labor market clears, and adjust the mean of the shocks to ensure that the total labor endowment is fixed. The complete set of combinations of $(\sigma_\epsilon, \sigma_\eta)$ is shown in Panel (A) of Figure 2.

Panel (B) of Figure 2 plots the model-predicted ξ, which changes with the fraction of the transitory component in the income shock process. In particular, ξ becomes smaller as the transitory component plays a larger role (equivalent to a larger σ_ϵ). If all of the dispersion in labor income is caused by transitory shocks, as assumed in Lee (2022), the model-predicted value of ξ under our calibration is much smaller (0.35) than in the data (0.50). This implies that the transitory income shocks cannot be the only source of labor income risk.

Lee does not discuss the impact of the assumption of only transitory shocks on the value of ξ. Instead, Lee directly estimates the value of ξ from the PSID data, and then uses this estimated value of ξ, together with the estimated change in the wealth distribution, to infer the parameters governing the income process. If we take Lee's approach in our model, i.e., searching for the value of σ_ϵ to target $\xi = 0.5$, we find that we need to set $\sigma_\epsilon = 1.22$ (Panel (C) of Figure 2). Then, standard deviation of labor earnings becomes unrealistically large (1.22 in the model and 0.82 in the data) under our calibration. We would suggest that Lee report some non-targeted moments of labor earnings to validate the assumption on the income shock process.

The relative importance of the persistent and transitory components of income shocks determines the consumption-savings choices by households, because households respond to transitory and persistent income shocks in different ways. Therefore, a realistic characterization of the income process is crucial to performing a counter-factual analysis and a welfare analysis. In addition, Braxton et al. (2021) show evidence that since the 1980s, persistent earnings risk has risen, while temporary earnings risk has declined. If a model assumes that there are no persistent shocks, the model will attribute the recent rise in inequality to an increase in transitory income risk, contrary to the empirical findings.

3.2 The Role of Income Shocks in Driving Wealth Inequality

What are the driving forces of the rise in wealth inequality? Using a reverse-engineering methodology, Lee assumes that the rise in wealth inequality is completely driven by the increase in income risk. This methodology basically calculates how much the changes in the

Table 3: Aggregate Implications of Different Sizes of Income Shocks

	Benchmark	Experiment 1		Experiment 2	
	Value	Value	Change	Value	Change
SD of persistent shocks	0.12	0.14	0.02	0.21	0.09
SD of log earnings	0.82	0.92*	0.10	1.40	0.58
Top 20% wealth share	0.67	0.70	0.02	0.80*	0.13
Consumption intensity	20.21%	19.36%	-0.85%	14.58%	-5.63%
Aggregate consumption	1.96	1.98	0.96%	2.06	5.13%
Aggregate wealth	7.75	8.26	6.58%	12.09	55.97%

Notes: The "benchmark" column reports the model statistics under our benchmark calibration, as explained in Table 1. The "wealth share" is defined as the quintile shares of wealth inclusive of income as reported in Table 1 of Lee (2022). Variables with a * denote the targeted moments of the experiment.

income shock parameters are needed to explain the observed rise in wealth inequality. In this section, we show that it is important to discipline the change in income risks because different factors that increase wealth inequality have quantitatively different impacts on aggregate consumption.

To show this point, we perform the following exercise. In Experiment 1, we increase the standard deviation of η_t from 0.12 to 0.14 to target the increase in the standard deviation of log earnings from 0.82 to 0.92, which is documented in Song et al. (2019). By doing so, we discipline the contribution of the change in income risks to exacerbating wealth inequality. As shown in Table 3, the wealth inclusive of income share of the top 20 percent of households increases from 67 percent to 70 percent, much lower than in the data (an increase to 80 percent), which suggests that other factors also play a role in shaping the wealth distribution. In this experiment, consumption intensity decreases, but by a much smaller size than in the data (0.85 percent in this experiment vs. 3 percent in the data reported in Lee (2022)).

In Experiment 2, we study the aggregate implications if we assume that the increase in income risks completely explains rising wealth inequality. To do so, we change the standard deviation of persistent shocks from 0.12 to 0.21 to target the change in the top 20 percent of the wealth inclusive of income share. As a result, the standard deviation of log earnings drastically increases to 1.40, much higher than in the data (0.92). This experiment suggests that Lee (2022) may overestimate the role of income shocks in driving wealth inequality.

Experiments 1 and 2 suggest two caveats about the conclusion that the rise in income risk results in a significant decrease in consumption intensity. First, is the decrease in consumption intensity driven by the decrease in aggregate consumption (numerator) or the increase in aggregate wealth (denominator)? Lee does not discuss this question. Instead, Lee assumes that aggregate wealth does not change and thus the decrease in consumption intensity is completely driven by the decrease in aggregate consumption. However, as shown in Table 3, in both Experiments 1 and 2, the decrease in consumption intensity is a result of an increase in aggregate wealth. Aggregate consumption slightly increases, contrary to the model predictions in Lee (2022). We will further discuss the drivers of the discrepancy between aggregate consumption and consumption intensity in Section 3.3.

Second, to what extent does the rise in income risks explain the rise in wealth inequality? What is the size of the increase in income risk? Experiment 1 shows that if we discipline it by the changes in the earnings distribution, the change in income risks cannot fully explain the rise in wealth inequality and its effect on consumption intensity is rather small. If we allow factors other than the increase in income risks to explain the rise in wealth inequality, the predicted change in consumption intensity might be much different.

3.3 The Shape of the Consumption Function

In a standard Aiyagari model with occasionally binding borrowing constraints, ξ is a structural parameter and depends on individual-specific state variables. However, Lee directly estimates the value of ξ from the PSID data and assumes that it applies to all households' consumption-savings decisions. In what follows, we show the differences between these two methods in characterizing individual consumption behaviors, which also leads to a discrepancy between aggregate consumption and consumption intensity.

First, in the left Panel of Figure 3, we plot the model-simulated individuals' consumption

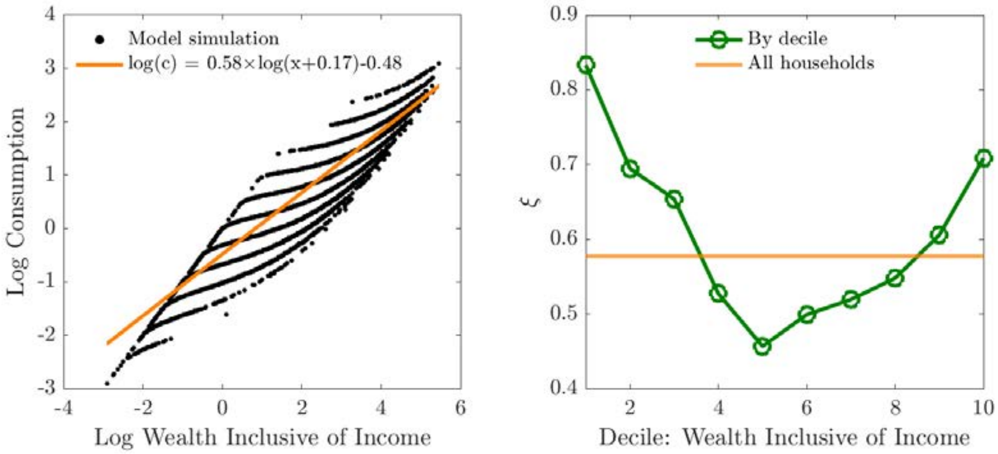

Figure 3: Estimate the Consumption Function: Constant vs. State-dependent ξ

against their wealth inclusive of income for all households. In addition, we plot the fitted line of an OLS regression. It shows that using a linear regression, the estimated ξ overstates the consumption of poor households and understate consumption of wealthy households.[4]

The comparison between the left panel of Figure 3 and the left panel of Figure 3 in Lee (2022), shows that a standard Aiyagari model matches the data well at the bottom of the wealth distribution. Specifically, both the data points and the model-simulated points are below the fitted regression line. However, the Aiyagari model overpredicts the consumption levels for households at the top level of wealth compared to those levels in the data.

To further illustrate how ξ depends on wealth levels, we sort households by their wealth inclusive of income into 10 groups, and estimate ξ for each group. The right panel of Figure 3 plots the estimated ξ for all households and for each decile. It clearly shows that ξ exhibits a U-shape. ξ is higher for households at the bottom of the wealth distribution, because a large fraction of them are at the borrowing constraint. This hand-to-mouth type of households consume all their cash on hand, meaning the slope of their consumption function is near 1. This type of household is well captured in an Aiyagari model.

The model-generated households at the top of the wealth distribution also have a high value of ξ, but for a different reason. Since rich households can better insure themselves

[4]This result holds even if we only allow for transitory shocks.

Table 4: Aggregate Predictions: Model vs. Estimated Consumption Function

	Model			Constant ξ		
	$\sigma_\eta = 0.12$	$\sigma_\eta = 0.21$	Change	$\sigma_\eta = 0.12$	$\sigma_\eta = 0.21$	Change
Aggregate consumption	1.96	2.06	5.13%	1.91	1.92	0.67%
Consumption intensity	20.21%	14.58%	-5.63%	19.62%	13.55%	-6.07%

against income risk, they have a weaker motive for precautionary saving. Since the precautionary saving motive is the only reason for households to save in a standard Aiyagari model, this type of households' marginal propensities to consume increase with wealth levels.

Does using a constant ξ lead to quantitative differences in aggregate predictions? To answer this question, we do the following calculation. First, we calculate the aggregate predictions of the stationary equilibrium of Experiment 2 in Table 3, which shows the model predictions of an increase in income risk under a state-dependent ξ. Next, we compute each household's consumption predicted under a constant ξ (and a constant ζ), in which the value of ξ (and ζ) is found by the OLS regression in Panel (a) of Figure 3. That is, we let each household's consumption follow

$$c_t = e^{0.58 \times log(x_t + 0.17) - 0.48}, \tag{3}$$

where x_t denotes wealth inclusive of income, and then aggregate using the same stationary distribution as the one computed from Experiment 2.

Table 4 shows that while assuming a constant ξ and allowing for a state-dependent ξ predict similar results for the change in consumption intensity, these two methods yield drastically different predictions on the change in aggregate consumption. When ξ is state dependent and is consistent with the standard Aiyagari model, a rise in wealth inequality leads to an increase instead of a decrease in aggregate consumption. This is because households at the top of the wealth distribution become wealthier and consume more after a rise in wealth concentration. Since the model-consistent ξ for this group of households is much higher than that for the average population (right panel of Figure 3), their changes in consumption drive the change in aggregate consumption. When assuming a constant ξ, however, the predicted change in aggregate consumption barely increases as wealth inequality rises, because the marginal propensities to consume of the wealthiest households are lower under a constant ξ than under model-consistent ξ. When consumption intensity and aggregate consumption move in opposite directions, which one affects the change in firms' R&D decisions? This question is not discussed in Lee (2022).

What is the best way to solve this problem? The original version of the Aiyagari model in which households save only due to the precautionary saving motive may not be able to give an answer. It is well documented in the literature that the standard Aiyagari model cannot explain the saving rates of wealthy households found in the data (De Nardi and Fella (2017) and Fagereng et al. (2019)). The existing literature has found several ways to resolve this problem, including, for example, introducing entrepreneurship (Cagetti and De Nardi (2006)) or non-homothetic preferences (Straub (2019)). This suggests that some other features need to be added before using an Aiyagari model to study the implications of the rise in wealth inequality experienced in the real world.

Lee circumvents this problem by using a reduced-form method and directly estimates this structural parameter, ξ. Although under this calibration, the consumption of rich households may match the data better than a standard Aiyagari model does, a reader might wonder about the structural differences between Lee's model and Aiyagari (1994). We would suggest that Lee provide a micro-foundation for the high savings rate of wealthy households, because it may have important welfare and policy implications.

4 Conclusion

How does rising wealth inequality affect economic growth? Lee studies this question by modeling an economy in which the demand side is described by a heterogeneous-agent model, and the supply side is characterized by a representative firm making optimal R&D decisions.

We focus our discussion on the quantitative results of Lee (2022). Namely, how much does the rising wealth inequality experienced in the US reduce consumption intensity and aggregate consumption? We calibrate the original Aiyagari (1994) model and the aggregate shocks following the standard approach in the literature. We then discuss the key differences in methodology and assumptions between Lee's approach and the standard approach. We further show how this methodological difference may change the quantitative effect of wealth inequality on aggregate consumption.

We provide three suggestions. First, it is important to incorporate the persistent components into the income shock process. Second, one needs to discipline the change in the income process rather than assuming that all of the rise in wealth inequality is due to an increase in income risks. Third, it would be helpful to provide a micro-foundation beyond the original Aiyagari model to resolve the inconsistency between the model-implied consumption concavity parameter and that of the data.

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