

Discussion of:
“Habits and Leverage”
by Tano Santos and Pietro Veronesi

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Outline

1 Set Up

2 Key Findings

3 Comments

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The Set Up

- Investors have heterogeneous initial wealth shares (w_i) and external habit preferences

$$u(C_{it}, X_{it}, t) = e^{-\rho t} \log \left(C_{it} - D_t \frac{b_i + a_i Y_t}{B + Y_t} \right),$$

where

$$\frac{dD_t}{D_t} = \mu_D dt + \sigma_D(Y_t) dZ_t$$

$$dY_t = k(\bar{Y} - Y_t)dt - \nu Y_t \left[\frac{dD_t}{D_t} - \mu_D dt \right], \quad \nu \geq 0$$

- The state Y is a “recession indicator” ($\sigma'_D(Y_t) > 0$, $\lim_{Y_t \downarrow \lambda > 1} \sigma_D(Y_t) = 0$)
- Y_t^{-1} akin to a “surplus consumption ratio”
- Risk sharing motivated by heterogeneous exposure to Y (low a_i /high $w_i \rightarrow$ high risk tolerance)
- Complete markets and aggregates to the representative agent of Menzly, Santos and Veronesi (JPE2004, MSV henceforth)

⇒ same pricing implications independently from heterogeneity.

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Key Findings

With only one state variable and no ad hoc frictions, can generate:

- ① MSV pricing (more on this coming)
- ② procyclical debt-to-output ratio, countercyclical debt-to-wealth ratio, stationary consumption shares (cf. heterogeneous R.A. models)
- ③ (some) poor agents borrow more than richer agents to increase consumption (low R.A. agents with low endowment).
- ④ aggregate leverage positively correlated with: valuation ratios, low future excess return, (good time = low Y_t = low R.A.), return vol (σ_D assumption), “consumption boom” (levered agents do particular well in good times)
- ⑤ deleveraging after negative shocks and “apparent” selling pressure ($\uparrow Y \rightarrow \uparrow R.A. \rightarrow \downarrow$ leverage and prices)
- ⑥ endogenous wealth dynamics and inequality (more on this coming).
- ⑦ and explain why leverage is a “priced” factor.

Baseline: I'm impressed – a new workhorse model (that satisfies Occam's razor).

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- MSV needs much more curvature than log to be consistent with asset implied bounds for the SDF
- ⇒ aggregation result holds with power function, and pricing implications can be “easily” computed numerically. Use that for quantitative part of the paper.

- MSV captures well the B.C. properties of the SDF but misses a jump like (market crash) component needed to be consistent with the data
- ⇒ the Y process ($\text{not } D$) could accommodate that.

Comment 2: wealth and inequality

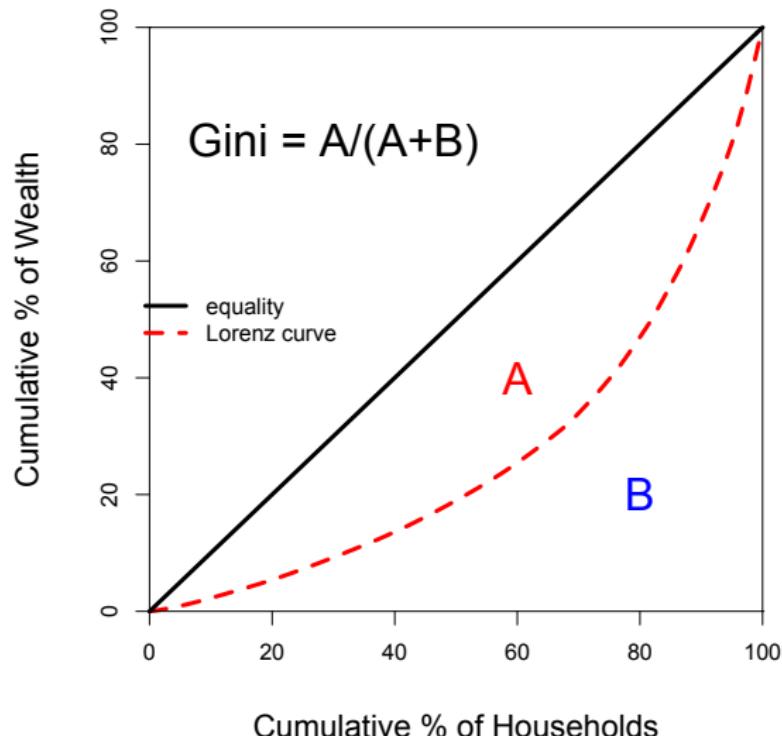
- Wealth shares are stationary and given by

$$\frac{W_i}{\int W_i di} = a_i + (w_i - a_i) \frac{(\rho + k) \bar{Y} Y_t^{-1}}{\rho + k \bar{Y} Y_t^{-1}}$$

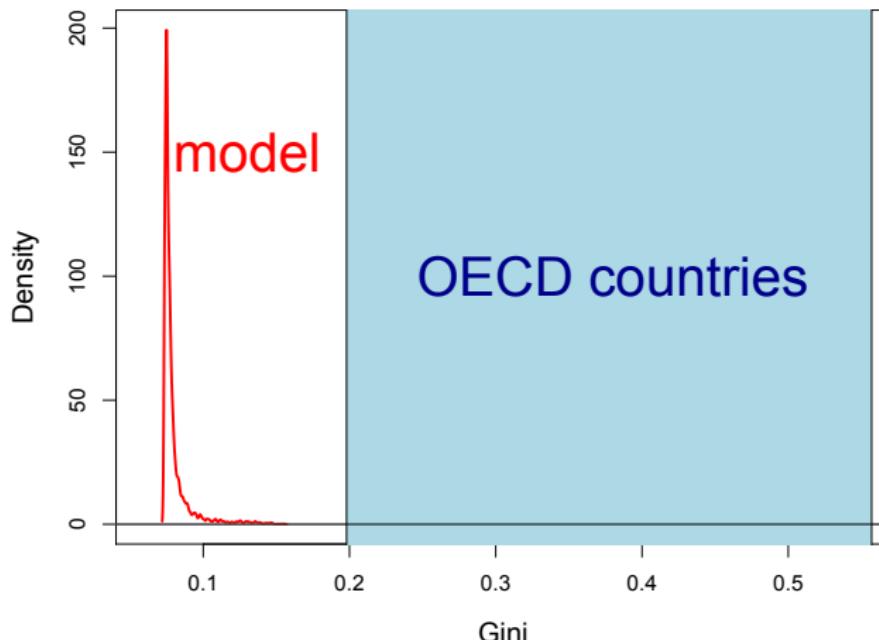
Note: agents with $(w_i - a_i) > 0$ (< 0) have positive (negative) leverage.

⇒ easy to compute inequality and cross-sectional wealth dynamics.

Reminder: the Gini measure of wealth inequality



The Gini coefficient distribution in the model

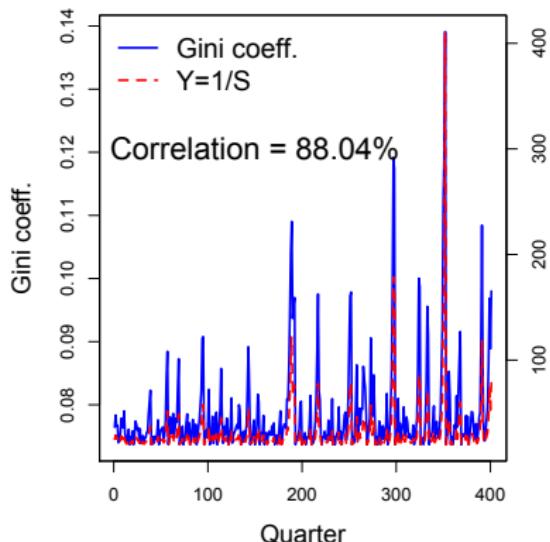


- ⇒ way too little wealth inequality generated by the model.
- could be fixed by either increasing the dispersion of:
 - a_i : ... but many agents would have very high R.A.
 - w_i : ... but inequality would become (even more) a B.C. variable

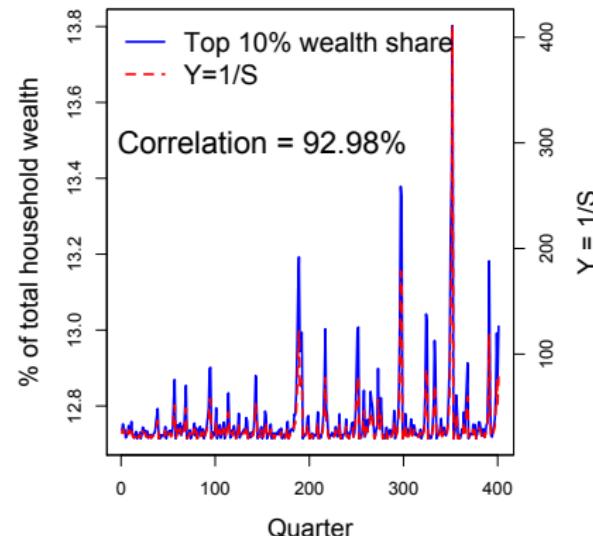
(more on this shortly)

Inequality and Business Cycle in the model

Gini and $Y=1/S$



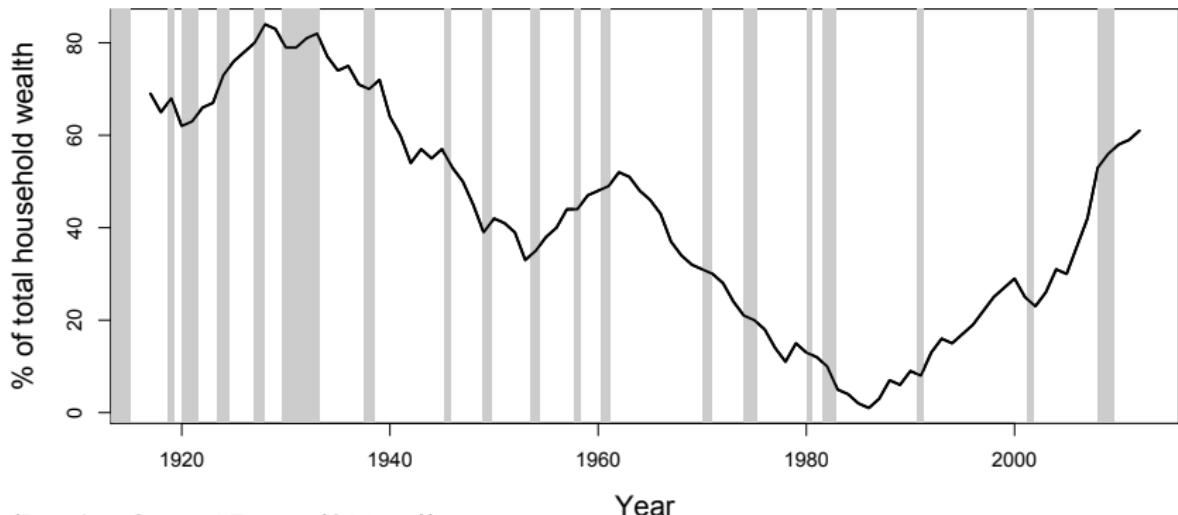
Top 10% wealth share and $Y=1/S$



- Inequality is a B.C. variable in the model (but in the data... next slide)
- The latent Y is almost perfectly correlated with the top wealth share
- ⇒ inequality is basically a “priced factor” since the s.p. density is log linear in Y

Inequality and Business Cycle in the data

U.S. top 10% wealth share



(Data from Saez and Zucman (QJE2016))

- (wrong level and) inequality is *not* really a B.C. variable in the data...
- ... and its first difference (or detrended component) has basically zero correlation with the B.C.

⇒ to match low frequency dynamic make \bar{Y} (slowly) time varying.

Note: similar problem for consumption inequality (but fewer data to compare).

Comment 3: heterogeneity in micro data

- ? a model with rich heterogeneity that does *not* target the heterogeneity in the data...
- Both latent state and R.A. heterogeneity can be recovered combining aggregate data and household consumption panel data (e.g. PSID, Constantinides-Ghosh (JF2017)):

$$C_{i,t} = \left[\frac{b_i + a_i Y_t}{B + Y_t} + \phi_i \right] D_t$$

Also: over-identified if combined with household wealth data.

Note: only care about distributions (not point estimates, i.e. much easier).

⇒ better quantitative implications targeting wealth and consumption distribution moments.

Note: quantities matter for understanding the relevance of the *frictionless* channel proposed.

... but might need frictions (à la Gomes and Michaelides (JF2005)) to match micro data ... but more realistic than the restrictions of most of the competing models.

- A brilliant new benchmark framework – I'll be teaching it to my students!
- Needs more (follow up) work to:
 - convince us of the *quantitative* relevance of the mechanism;
 - become (more) consistent with pricing, wealth and micro data.