Discussion of:

"A Stochastic Discount Factor Approach to Asset Pricing Using Panel Data Asymptotics"

by

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Summary

- New econometric nonparametric estimator of the SDF based on panel-data asymptotic: Araujo Issler (AI) SDF.
- Contribute to a large literature started by Hansen and Jagannathan (HJ, 1991), where nonparametric SDFs are used to diagnose models, test predictability, performance analysis, ...
  - On each state, the AI SDF is proportional to the inverse of the geometric mean of cross sectional returns.
  - Main advantage with respect to HJ and its variations is the simplicity of estimation for a large number of assets. However, ...
  - it comes with a cost of introducing large pricing errors, **but not much larger than the errors achieved by previously proposed SDFs**.
- Empirical application: Tests of parametric SDFs by projections on their proposed SDF.

Comparisons with the Literature

- The AI nonparametric SDF should be compared to a number of other previously proposed nonparametric/semiparametric SDFs:
  - 1) Nonparametric Hansen and Jagannathan (1991) linear SDF with positivity constraint, and all its generalizations with conditional variables
  - 2) Nonlinear SDF by Bansal and Viswanathan (1993) obtained with Logistic Functions
  - 3) Taylor expanded SDF by Dittmar (2002)
  - 4) Stutzer (1995) exponential, Growth portfolio SDF by Bansal and Lehman (1997)
- Most of these SDFs present small/zero pricing errors and are also based on economic theory.

The AI SDF is too smooth: It is not Admissible

- The AI SDF presents high pricing errors, and I believe this is the reason for why the Equity Premium Puzzle disappears!

- An important diagnostic test: See if the SDF is above the HJ variance bound with positivity constraint.
  - As I show below, this is not the case. The sample volatility of the AI SDF (0.0215) is 16 times smaller than the volatility of the HJ SDF with pos. constraint (0.3588)!

- The AI SDF is not useful to test parametric SDFs like the CCAPM by projections since it already does not explain a significant amount of information on returns.

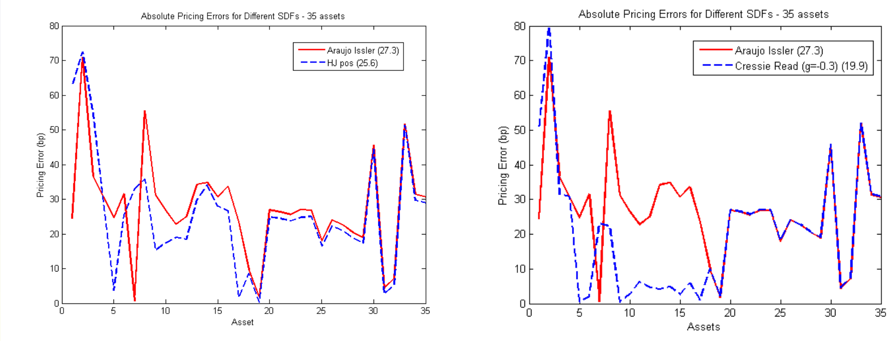
- But it is still a good approximation for an admissible SDF when the number of assets is large.

Robustness of Results: Comparison with HJ with positivity constraint

- HJ propose a linear SDF with positivity constraint that is simple to estimate, if the number of assets is not too large
  - This SDF also introduce pricing errors when the number of priced assets increase.
  - The HJ estimator becomes harder to solve when the number of priced assets increase.
- Therefore, an effective comparison is fundamental to understand the advantages and drawbacks of the new methodology.
  - Extracting the risk-free rate, analyzing the pricing errors from Euler equations, pricing out-of-sample in the panel, etc...
- I compare the AI SDF with the HJ SDF with positivity constraint and with some other SDFs.

Euler Equation Pricing Errors

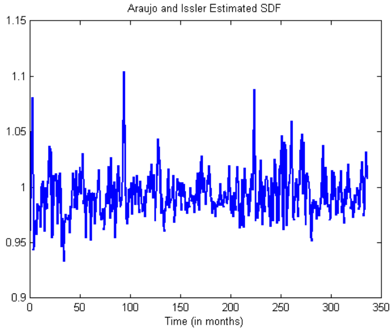
- SDFs should satisfy the Euler Equation for the returns R: $E[mR] = 1$

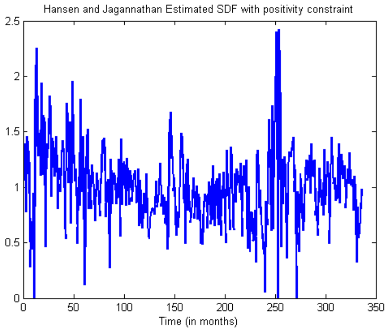


Comparing SDF's Shape

- The HJ SDF is much more volatile than the AISDF: 0.3588 x 0.0215

- The absolute average pricing errors are a bit smaller: 25.6 bp x 27.3 bp

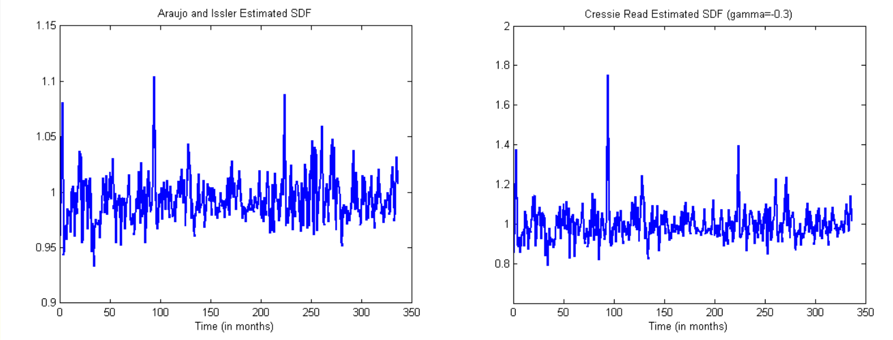




Comparing SDF's Shape

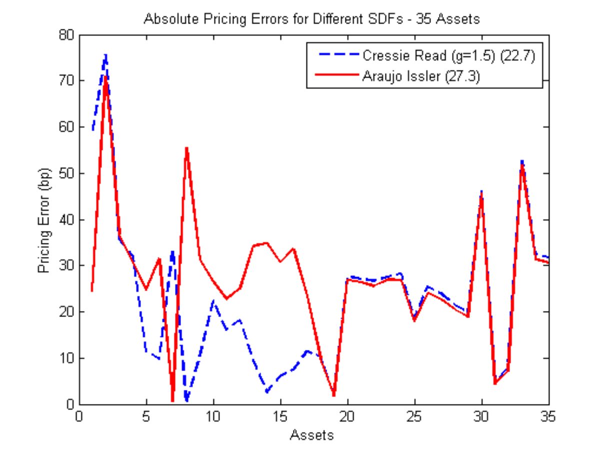
- The CR ($\gamma = -0.3$) SDF is more volatile than the AISDF: 0.0877 x 0.0215

- The absolute average pricing errors are much smaller: 19.9 bp x 27.3 bp



More on Euler Equation Pricing Errors

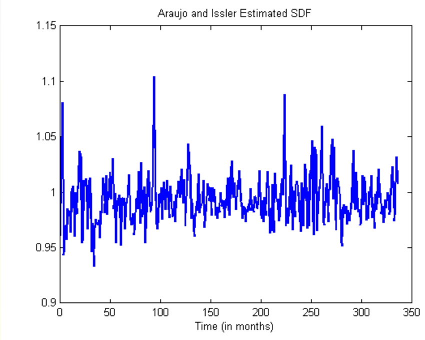
- SDFs should satisfy the Euler Equation for the returns R: $E[mR] = 1$

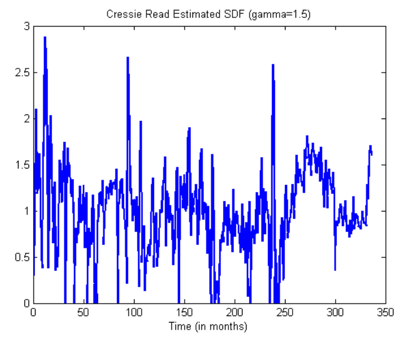


Comparing SDF's Shape: Much more volatility...

- The CR ($\gamma = 1.5$) SDF is much more volatile than the AISDF: 0.4774 x 0.0215

- The absolute average pricing errors are smaller:22.7 bp x 27.3 bp





Obtaining An Infinity of Positive Semi-parametric SDFs Based on Nonlinear Projections

- Almeida and Garcia (2010) solve SDF nonlinear projection problems where the discrepancy functions (distances) are based on members of the Cressie Read family.
- Implied SDFs are obtained from the first order conditions of portfolio problems based on HARA utility functions.
- The implied SDFs are strictly positive hyperbolic functions of the primitive returns, and admissible, that is, perfectly price the primitive assets:

$$\hat{m}_{MD}(R) = \beta * \left(1 + \gamma \hat{\lambda}'_{opt}\left(R - \frac{1}{a}\right)\right)^{\frac{1}{\gamma}} \tag{1}$$

- Include Stutzer (1995) exponential, Growth portfolio SDF by Bansal and Lehman (1997), and HJ (1991) as particular cases

Conclusion

- AI SDF is simple to estimate and presents pricing errors comparable to other well known nonparametric SDFs.
- In particular, it has volatility too small, much smaller than the minimum volatility required for an SDF to be admissible.
- On the other hand, most estimated SDFs, in a context of a large number of assets, are much harder to obtain and also present large pricing errors.
- AI SDF appears to be a particularly promising candidate to give approximately right prices when there is a large set of assets.