

How risky is consumption in the long-run? Benchmark estimates from a novel unbiased and efficient estimator

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- A large literature studies how risky the economy is
- For Epstein–Zin preferences, correct measure is *long-run standard deviation* (LRSD) of consumption growth
- Estimating the LRSD is difficult
- This paper:
 - Develops novel non-parametric estimator
 - Estimates LRSD with data back to 1834

Epstein–Zin preferences:

$$V_t = \left\{ (1 - \beta) C_t^{1-\rho} + \beta E_t [V_{t+1}]^{\frac{1-\rho}{1-\alpha}} \right\}^{\frac{1}{1-\rho}}$$

ρ : inverse EIS

α : risk aversion

- Price of risk (through the HJ bound) depends on volatility of the SDF
- Assume log-normal, homoskedastic consumption growth
- Standard deviation of the SDF:

$$\text{std}(M_{t+1}) \approx \text{std} \left(\rho \Delta E_{t+1} \Delta c_{t+1} + (\alpha - \rho) \Delta E_{t+1} \sum_{j=0}^{\infty} \beta^j \Delta c_{t+1+j} \right)$$

(exact with unit EIS)

Δc_t : log consumption growth

Pricing kernel

Let $\beta \rightarrow 1$

$$\text{std}(M_{t+1}) \approx \text{std} \left(\rho \Delta E_{t+1} \Delta c_{t+1} + (\alpha - \rho) \Delta E_{t+1} \underbrace{\sum_{j=0}^{\infty} \Delta c_{t+1+j}}_{LRSD} \right)$$

- News about $\sum_{j=0}^{\infty} \Delta c_{t+1+j}$ is news about $c_{t+\infty}$
- Most calibrations: $\alpha \gg \rho$

$$\text{std}(M_{t+1}) \approx \alpha \times LRSD$$

- Implies the long-run component dominates
 - Long-run risk model is about making $\Delta E_{t+1} \sum_{j=0}^{\infty} \theta^j \Delta c_{t+1+j}$ very volatile
- *LRSD* is key to calibrating any model with Epstein–Zin preferences

Recent calibrations

Table 1. Recent calibrations of the long-run standard deviation of consumption growth (annualized)

	<u>Long-run SD</u>	<u>Moments matched</u>
Campbell and Cochrane (1999)	1.50	SD(dc) 1947-1995
Gouio (2010)	2.00	SD(TFP), 1947-2010
Barro(2006), Wachter (2010)	2.00	SD(dy) 1954-2004, international
Tallarini (2000)	2.30	SD(dc), 1948-1993
Mehra and Prescott (1985)	3.16	SD(dc) 1889-1978
Boldrin, Christiano, and Fisher (2001)	3.60	Various unconditional SDs, 1964-1988
Abel (1990)	3.60	SD(dc) 1889-1978
Barberis, Huang, and Santos (2001)	3.80	SD(dc), 1889-1985
Bansal, Kiku, and Yaron (2008)	4.54	Annual SD(dc), autocorrelations, 1929-2008
Drechsler and Yaron (2011)	4.83	Annual SD(dc), autocorrelations, 1929-2006
Campanale, Castro, and Clementi (2010)	5.20	SD(dy), 1947-2005
Bansal and Yaron (2004); Croce, Lettau, and Ludvigson (2010)	6.28	Annual SD(dc), autocorrelations, 1929-1998
Croce (2010)	8.05	Annual SD(dTFP), 1947-2010
Kaltenbrunner and Lochstoer (2010)	8.22	SD(dc), SD(dc)/SD(dy)
Colacito and Croce (2011)	9.02	SD(dc), currency movements

- LRSD appears frequently in econometrics:
 - LRSD is the std. dev. of innovations to the Beveridge–Nelson trend (martingale component of c_t)
 - LRSD determines standard errors in OLS and GMM (e.g. Newey–West estimator)
 - Square root of spectral density at frequency zero
- Large literature on estimating LRSD

Smoothed periodogram

- Spectral density is $f(\omega)$

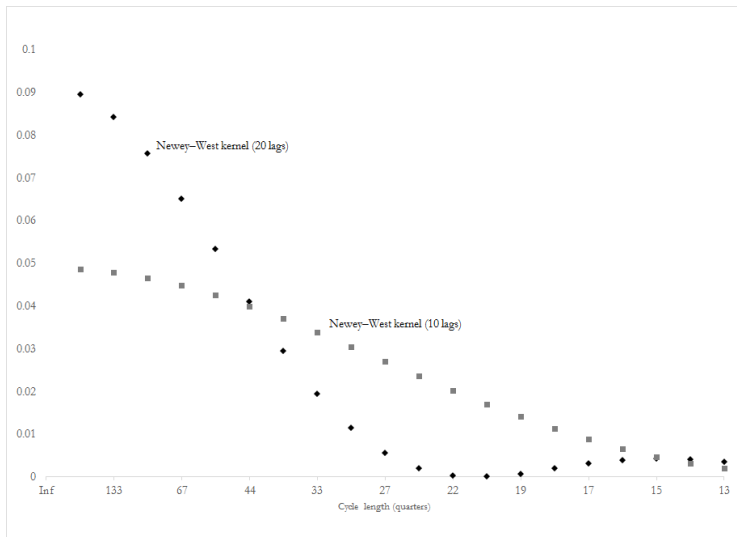
$$LRSD = \sqrt{f(0)}$$

Need to estimate $f(0)$

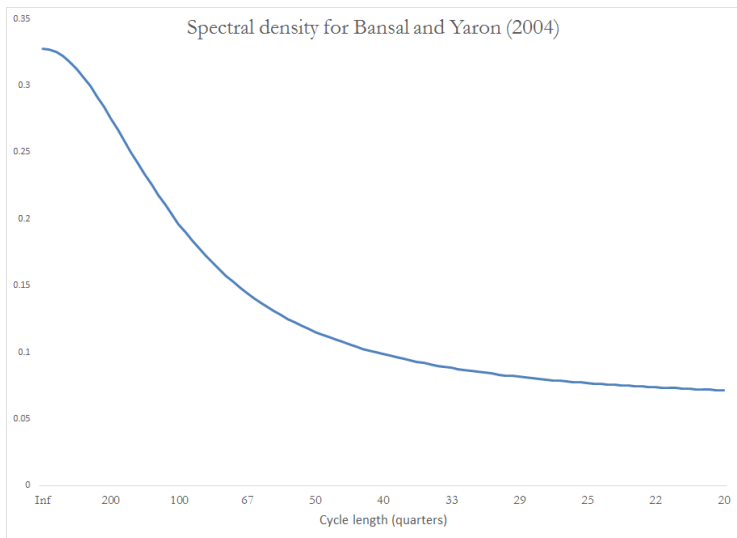
- Periodogram is the sample spectrum
 - Defined only at $T - 1$ frequencies
 - Measured with error
- Smoothed periodogram estimator:

$$\hat{f}(0) = \sum_{k=0}^{T-1} K(\omega_k) p(\omega_k)$$

Spectral Kernels



Benchmark model has strongly peaked spectrm

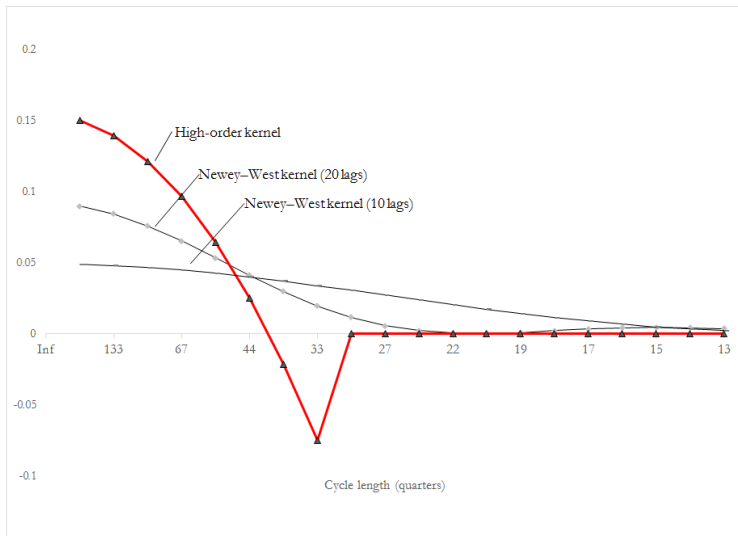


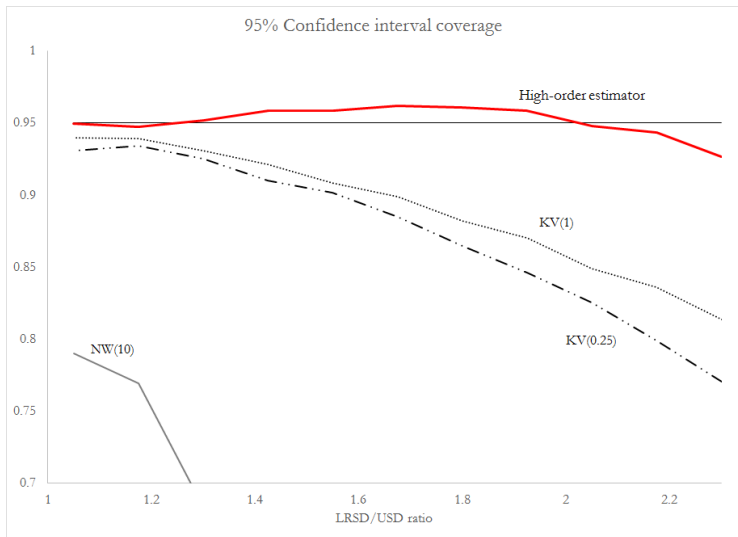
$$\begin{aligned} \text{bias} &\approx \frac{1}{2} f''(0) \int_{-\pi}^{\pi} \omega^2 K(\omega) d\omega \\ \text{variance} &\approx \frac{4\pi}{T} f(0)^2 \int_{-\pi}^{\pi} K(\omega)^2 d\omega \end{aligned}$$

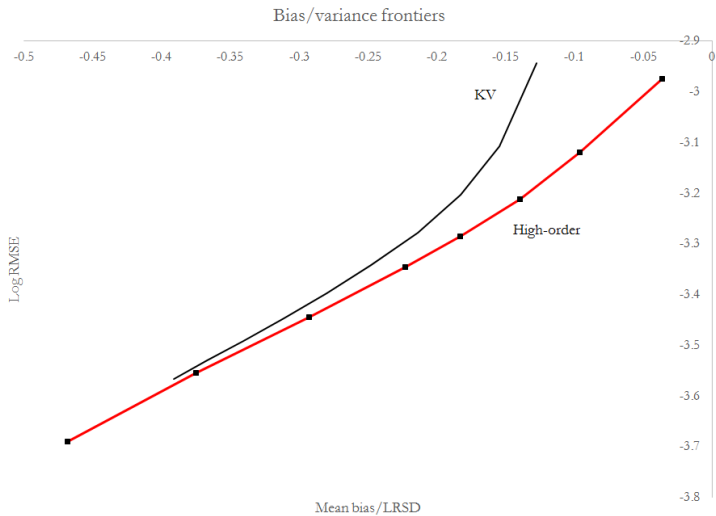
- More peaked kernel:
 - Reduces bias
 - Increases variance
- Changing NW lag length moves along bias/variance tradeoff
- Can we expand the frontier? Yes.

$$\begin{aligned} \text{bias} &\approx \frac{1}{2} f''(0) \int_{-\pi}^{\pi} \omega^2 K(\omega) d\omega \\ \text{variance} &\approx \frac{4\pi}{T} f(0)^2 \int_{-\pi}^{\pi} K(\omega)^2 d\omega \end{aligned}$$

- If $K(\omega)$ can be negative, can set approx. bias to zero
- This paper:
 - Set bias to zero
 - Minimize variance
 - Similar to Epanechnikov kernel
- Call it the "high-order kernel"
 - Can then extrapolate to low frequencies
 - Yields lower bias given variance



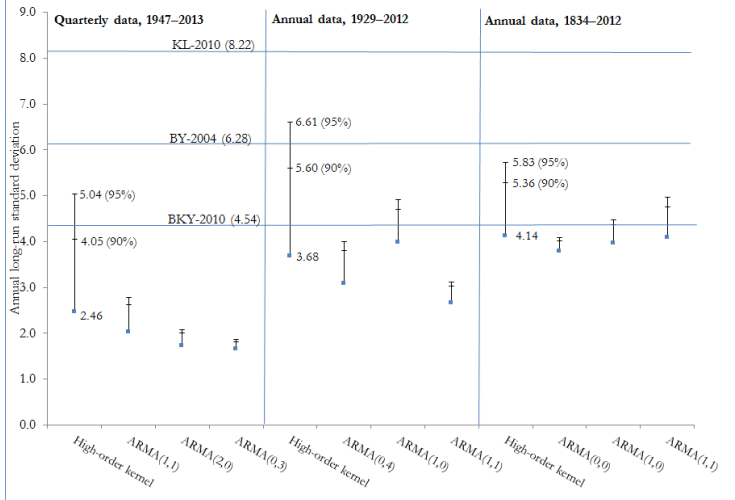




- High-order estimator yields:
 - Almost exact CI coverage
 - Superior bias/variance tradeoff

- Now apply high-order estimator to the data
- Three samples:
 - Post-war quarterly
 - Post-1929 annual
 - Post-1834 annual (Barro and Ursua)

Long-run standard deviation estimates and confidence intervals

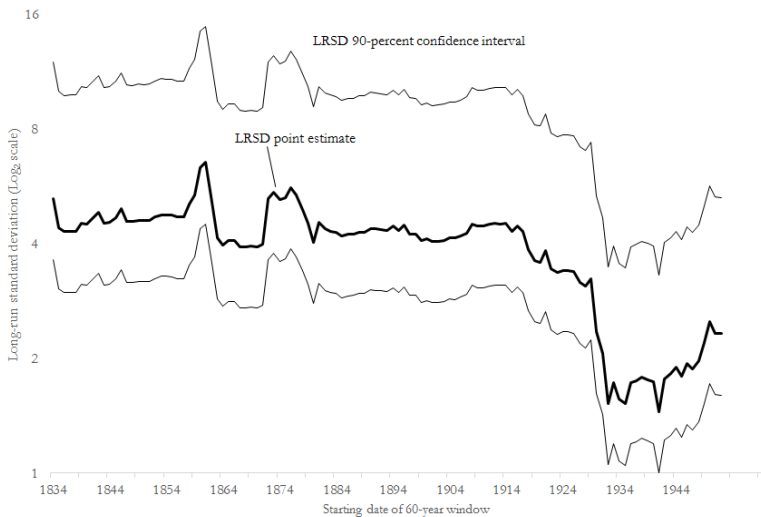


- Full-sample point estimate: 4.14% per year
- Post-war data much less volatile
- Conservative LRR calibrations look reasonable
- Parametric estimators yield *much* tighter CI

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Figure 4. Rolling LRSD estimates, 60-year window



Conclusion

- Long-run standard deviation is key moment for models with Epstein–Zin preferences
- Develop novel estimator: lower variance, better confidence interval coverage
- Delivers benchmark estimates of LRSD