



THE PERFORMANCE OF CHARACTERISTIC-SORTED PORTFOLIOS: EVALUATING THE PAST AND PREDICTING THE FUTURE

Aydoğın Altı, Travis L. Johnson, and Sheridan Titman

Spring 2022

Performance of Characteristic-Sorted Portfolios

Annualized Sharpe Ratios for value-weighted portfolios (*t*-stats in parenthesis)

	All	1963 – 1991	1991 – 2019	Difference
Value	0.32 (2.37)	0.42 (2.23)	0.22 (1.15)	-0.20 -(0.75)
Investment	0.44 (3.31)	0.44 (2.30)	0.45 (2.35)	0.02 (0.06)
Profitability	0.47 (3.48)	0.36 (1.89)	0.57 (2.96)	0.20 (0.75)
Size	0.02 (0.17)	0.10 (0.54)	-0.07 (-0.37)	-0.17 -(0.64)

The Big Questions

- The **positive (frequentist)** questions
 - Do expected returns of characteristic-sorted portfolios vary over time?
 - When we account for time-variation in expected returns, are we still confident that *unconditional* expected returns differ from zero?
- The **normative (Bayesian)** questions
 - How much should we tilt our portfolios towards characteristics like value and profitability?
 - To what extent should these tilts change over time as we learn from data?

What Do We Do?

- Propose a **statistical model** that accounts for the possibility that portfolio returns may be persistent
- Consistent with both **rational** and **behavioral** explanations for the abnormal returns associated with characteristics, e.g., the value premium
 - Risk exposures may change over the business cycle
 - Waves of “irrational exuberance” that relate to the introduction of new technology
 - Shiller (2000) and Alti and Titman (2019)
- We apply the model for **value**, **profitability**, **investment** and **size** portfolios
 - Adjust t -stats for **OLS** given persistence parameters
 - Estimate model parameters with **maximum likelihood**
 - **Bayesian** analysis with prior beliefs about parameters

Statistical Model

A time-series of market-neutral portfolio returns r_t satisfies

$$r_{t+1} = \mu_t + \epsilon_{t+1}$$

$$\mu_{t+1} = \mu + \lambda(\mu_t - \mu + \delta_{t+1})$$

with normally distributed unexpected return shocks ϵ_{t+1} and expected return shocks δ_{t+1}

- Model implies realized returns are jointly normal with autocorrelations:

$$\text{Corr}(r_t, r_{t-l}) = \lambda^{l-1} \gamma$$

- γ is the one-period return autocorrelation
- λ determines the decay rate of autocorrelations over time
 - We express λ in terms of H , the half-life of shocks to μ_t

Note, we are estimating the mean and the persistence of an unobservable variable, μ_t , but we only observe the time-series of r_t

Findings

1. The interpretation of historical mean returns depends on the persistent variation of conditional expected returns
 - With plausible levels of persistent variation standard errors double (relative to iid)
 - There is less independent variation in returns when expected returns are persistent
 - The data tell us very little about the magnitude of persistent variation

⇒ Our inferences are thus ultimately determined by the assumptions

2. Investors' posterior beliefs about expected returns are highly dependent on their priors about persistent variation
 - Applies to conditional as well as unconditional expected returns
 - E.g. Value's conditional Sharpe Ratio in 2020 is **0.29** for investors who believe returns are i.i.d. and **0.05** for investors who believe conditional expected returns vary with a 5-year half life

Autocorrelation Estimates

Estimate autocorrelation using regressions of the form

$$r_t = a + b \cdot \left(\frac{1}{4} \sum_{l=1}^4 r_{t-l} \right) + \epsilon_t$$

	Value	Investment	Profitability	Size	Pooled	Pooled (no size)
\hat{b}	0.19	0.21	0.21	0.47	0.30	0.20
iid t -stat	(1.61)	(1.74)	(1.80)	(3.70)	(4.43)	(2.97)

Result 1: prior-year returns positively predict next-quarter, strongest for size, others marginal

Result 2 (in paper): cannot reject highly persistent variations ($H = 10$)

Model-Based Standard Errors

- Any λ , γ , and sample size T implies a standard error correction for OLS estimates of μ :

$$SE(\hat{\mu}^{OLS}) = \frac{\sigma_r}{\sqrt{T}} \sqrt{1 + 2\gamma \frac{\lambda^T + T(1 - \lambda) - 1}{T(1 - \lambda)^2}} \approx \frac{\sigma_r}{\sqrt{T}} \sqrt{1 + \frac{2\gamma}{1 - \lambda}}$$

- Same intuition as Newey-West: \uparrow autocorrelation $\Rightarrow \uparrow$ standard errors
- Newey-West doesn't work in this context if H/T is large
- Analytically derived from the model with assumed parameters

Model-Based Standard Errors

	Value	Investment	Profitability	Size
$\hat{\mu}$	4.37	4.72	4.91	0.35
Unadjusted t -stat	(2.39)	(3.34)	(3.54)	(0.17)
Newey-West t -stat (10 lags)	(2.35)	(2.90)	(3.33)	(0.12)
Newey-West t -stat (20 lags)	(2.35)	(3.04)	(3.71)	(0.11)
Newey-West t -stat (40 lags)	(2.41)	(3.23)	(3.48)	(0.12)
Model t -stat ($H = 2.5, \gamma = 2.5\%$)	(1.83)	(2.56)	(2.71)	(0.13)
Model t -stat ($H = 2.5, \gamma = 5\%$)	(1.54)	(2.15)	(2.28)	(0.11)
Model t -stat ($H = 2.5, \gamma = 10\%$)	(1.23)	(1.71)	(1.81)	(0.09)
Model t -stat ($H = 5, \gamma = 2.5\%$)	(1.58)	(2.21)	(2.34)	(0.11)
Model t -stat ($H = 5, \gamma = 5\%$)	(1.26)	(1.77)	(1.87)	(0.09)
Model t -stat ($H = 10, \gamma = 2.5\%$)	(1.34)	(1.87)	(1.98)	(0.10)
Model t -stat ($H = 10, \gamma = 5\%$)	(1.03)	(1.44)	(1.53)	(0.07)

Result: t -stats half as large for reasonable H and γ

Maximum Likelihood Hypothesis Testing

Estimate (H, γ) jointly with μ using max likelihood, test $\mu = 0$ restriction using **likelihood ratio test**

	Const μ	Evolving μ				$\mu = 0$ <i>p</i> -value
	$\mu = 0$ <i>p</i> -value	\hat{H} (years)		$\hat{\gamma}$ (%)		
		Unrest.	$\mu = 0$	Unrest.	$\mu = 0$	
Value	1.8%	14.9	20.0	-0.6%	2.7%	10.2%
Investment	0.1%	9.4	14.7	-0.9%	5.3%	5.7%
Profitability	0.0%	20.0	20.0	-0.4%	4.5%	5.7%
Size	86.3%	1.3	2.2	15.4%	14.8%	37.8%

Result: evidence against $\mu = 0$ weaker when allowing time-variation

- Data could reflect persistent but temporary μ_t (large H and γ)

Summary of Frequentist Evidence

- If we fix reasonable model parameters, standard errors can be 50% to 100% larger than Newey-West
- If we estimate model parameters freely, $\mu = 0$ & $H \gg 0$ fits data well enough for $\mu = 0$ p -value to be above 5% even when iid p -value is 0.1%
- When many different assumptions, all consistent with the data, lead to substantially different conclusions, natural to use a **Bayesian** approach that integrates across reasonable parameter values weighted by priors

Bayesian Estimation

1. Specify priors over model parameters, e.g., μ and H
2. Compute posterior beliefs about model parameters based on priors + data
 - Using full sample
 - Using past returns only at the end of each calendar year
3. Using posterior distribution of parameters, compute informative moments
 - Conditional and unconditional expected returns & Sharpe Ratios
 - Optimal portfolio allocations for CRRA investors

Bayesian Findings

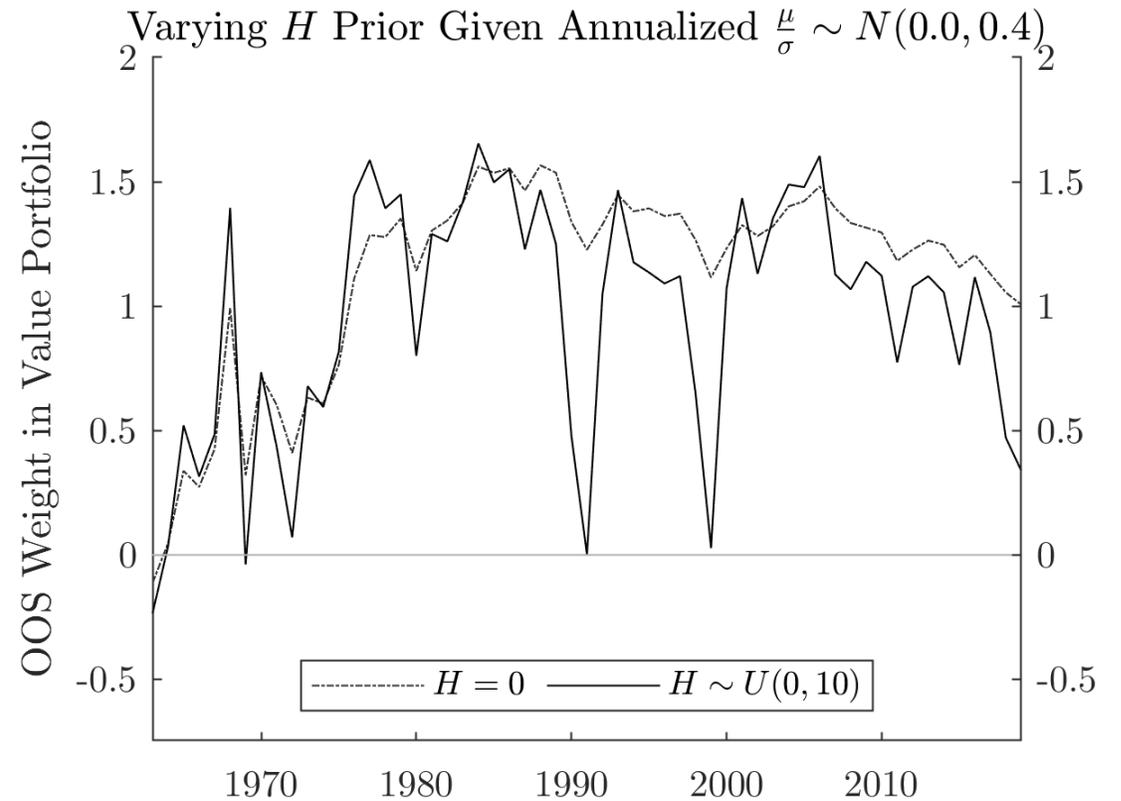
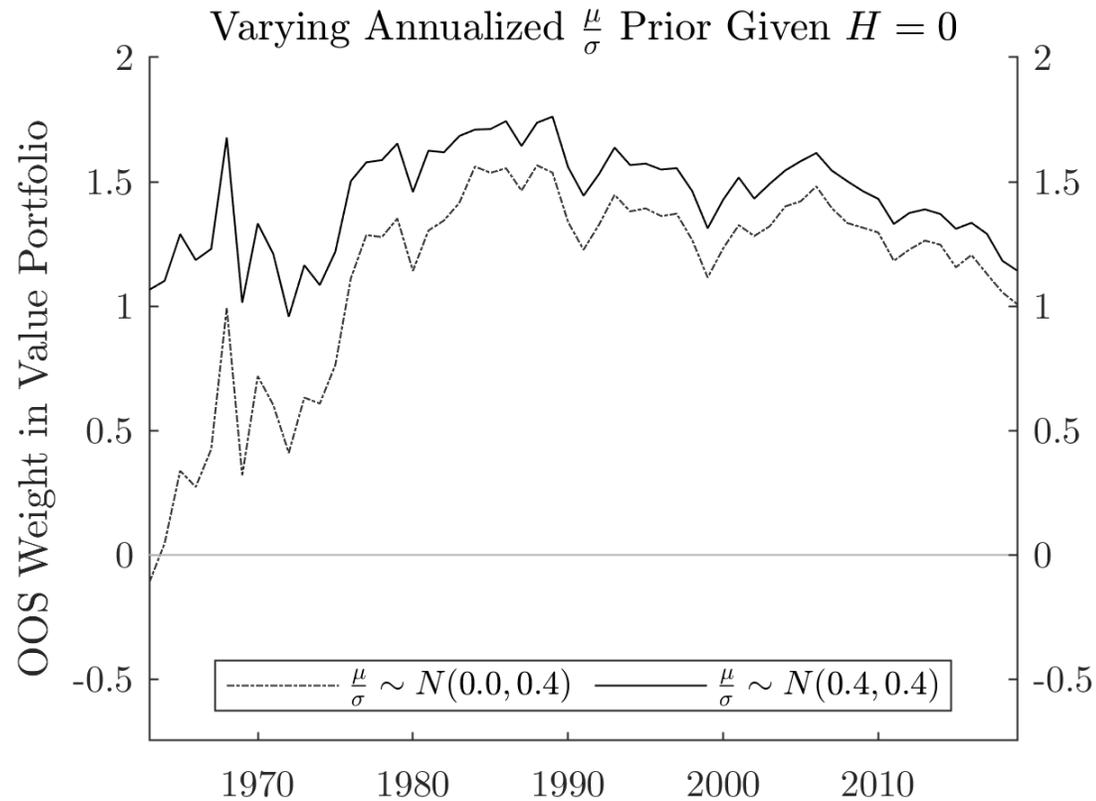
Investor believes that returns are i.i.d. ($H = 0$)

- Priors about unconditional expected returns matter little after observing 56 years of data
- Posteriors about unconditional expected returns are measured more precisely
- Posteriors in about expected returns depend equally on the entire history, e.g. in 2020:
 - Tilts towards profitable value firms
 - No size tilt

Investor considers possibility that conditional expected returns are time-varying ($H > 0$)

- Priors about unconditional expected returns still matter after observing 56 years of data
- Posteriors about unconditional expected returns are very uncertain
- Posteriors about conditional expected returns follow recent trends, e.g. in 2020:
 - Tilts towards large and profitable firms
 - No value tilt

Out-of-sample learning and timing for Value



Result 1: disagreement about μ resolves quickly when $H = 0$

Result 2: disagreement about H leads to large, permanent differences in the intensity of timing

Conclusions

1. Characteristic-sorted portfolios are likely to exhibit persistent time-variations in expected returns, ignoring this will produce **false positives**
 - Potential explanation for “factor zoo”
 - Can also produce **false negatives**, e.g., there may be a large unconditional size premium
2. Cannot precisely detect the degree of persistent variation in expected returns
 - Our estimates indicate that Bayesians will **follow trends** anyway
3. **Priors matter much more if returns are potentially persistent**
 - Disagreement and motive for trading
4. These issues are relevant for the evaluation of any portfolios
 - Evidence of superior mutual fund performance
 - Returns of stocks of firms headquartered in some cities outperform stocks from other cities