Anomalies and the Expected Market Return

Dong, Li, Rapach, and Zhou (2022)

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  - Whether firm characteristics can predict the cross-sectional dispersion in stock returns
  - The time-series predictability of the aggregate market excess return based on a variety of economic and financial variables
- This paper investigates whether these two leading lines of the finance literature are linked
  - The ability of long-short anomaly portfolio returns from the cross-sectional literature to predict the market excess return

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  - examines 100 long-short anomaly portfolios
  - applies a variety of shrinkage techniques—including machine learning, forecast combination, and dimension reduction—to guard against overfitting the data in a high-dimensional setting.
  - finds long-short anomaly returns strongly negatively predict the market return. The out-of-sample R^2 (R^2_{OS}) statistics are economically sizable, ranging from 0.89% to 2.81%.

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- Assume that the long and short legs together comprise the market. Then

$$r_{M,t} = f_t + 0,5(\Delta u_{L,t} + \Delta u_{S,t})$$

Data-Generating Process

- According to the Wold representation theorem, the stationary component in each leg related to mispricing (i.e., the pricing error) can be expressed as

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- Example: $\psi_{S,1} = 0.9, \psi_{S,2} = 0.9, \psi_{S,j} = 0.9$ for $j \geq 3$
- Taking the first difference of equation above, we obtain the expression for the change in mispricing

$$\Delta u_{l,t} = \sum_{j=0}^{\infty} \tilde{\psi}_{l,j} v_{l,t-j} \quad \text{for } l = L, S$$

where $\tilde{\psi}_{l,0} = \psi_{l,0} = 1$ and $\tilde{\psi}_{l,j} = \psi_{l,j} - \psi_{l,j-1}$ for $j \geq 1$. Assume $\tilde{\psi}_{l,j} \leq 0$.

Mispricing Correction Persistence

- Consider a predictive regression relating the long- or short-leg return of the anomaly portfolio to next period's market return

$$r_{M,t+1} = \alpha_I + \beta_I r_{I,t} + \varepsilon_{I,t+1} \quad \text{for } I = L, S$$

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Mispricing Correction Persistence

- Consider a predictive regression relating the long- or short-leg return of the anomaly portfolio to next period's market return

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- We can also get

$$cov(\Delta u_{l,t+1}, \Delta u_{l,t}) = \left[(\psi_{l,1} - 1) + \sum_{j=1}^{\infty}(\psi_{l,j} - \psi_{l,j-1})(\psi_{l,j+1} - \psi_{l,j})\right] var(v_{l,t})$$

$$\text{for } l = L, S$$

Mispricing Correction Persistence

- We can write the changes in the level of mispricing for the current and next period as

$$\Delta u_{l,t} = v_{l,t} + \sum_{j=1}^{\infty} (\psi_{l,j} - \psi_{l,j-1}) v_{l,t-j} \quad \text{for } l = L, S$$

$$\Delta u_{l,t+1} = v_{l,t+1} + (\psi_{l,1} - 1) v_{l,t} \sum_{j=2}^{\infty} (\psi_{l,j} - \psi_{l,j-1}) v_{l,t-j} \quad \text{for } l = L, S$$

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- The consecutive changes in mispricing due to a **new overpricing shock** can generate **negative** serial dependence in the short-leg return. In contrast, **old pricing shocks** can produce **positive** serial dependence in the short-leg return.

Mispricing Correction Persistence

- Looking back to the covariance equation

$$cov(\Delta u_{I,t+1}, \Delta u_{I,t}) = \Big[(\psi_{I,1} - 1) + \sum_{j=1}^{\infty} (\psi_{I,j} - \psi_{I,j-1})(\psi_{I,j+1} - \psi_{I,j})\Big] var(v_{I,t})$$

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$$\text{for } I = L, S$$

- For it to be the case that $cov(\Delta u_{I,t+1}, \Delta u_{I,t}) > 0$, the return **momentum** generated by the correction of the overpricing induced by old shocks needs to outweigh the magnitude of the return **reversal** generated by the immediate correction of the overpricing induced by a new shock.

$$\sum_{j=1}^{\infty}(\psi_{I,j} - \psi_{I,j-1})(\psi_{I,j+1} - \psi_{I,j}) > -(\psi_{I,1} - 1)$$

Mispricing Correction Persistence

- Next, consider a predictive regression based on the long-short anomaly portfolio return

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- We get the standardized slope coefficient

$$\tilde{\beta}_{LS} = \frac{0.5[cov(\Delta u_{L,t+1}, \Delta u_{L,t}) - cov(\Delta u_{S,t+1}, \Delta u_{S,t})]}{\left[var(\Delta u_{L,t}) + var(\Delta u_{S,t})\right]^{\frac{1}{2}}}$$

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- Empirically, the paper finds that $\tilde{\beta}_{LS} < 0$, which holds when

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$$cov(\Delta u_{S,t+1}, \Delta u_{S,t}) > cov(\Delta u_{L,t+1}, \Delta u_{L,t})$$

- This is achieved when there is stronger MCP with respect to overpricing than underpricing (e.g. short-sale impediments).

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Forecast Construction

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- The prevailing mean forecast is simply the average of the market excess return observations available at the time of forecast formation.

Forecast Construction

- The paper compares the prevailing mean benchmark to the seven forecasts summarized below
  - Conventional OLS
  - ENet
  - Simple Combination
  - Combination ENet
  - Predictor Average
  - Principal Component
  - PLS

Forecast Evaluation: Statistical Accuracy

- The paper first assesses market excess return forecasts in terms of statistical accuracy via MSFE

$$\hat{e}_{0,t|t-1} = r_{M,t} - \hat{r}^{PM}_{M,t|t-1}$$

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- The sample MSFE is given by

$$M\hat{S}FE_j = \frac{1}{T}\sum_{t=1}^{T} \hat{e}^2_{j,t|t-1} \quad \text{for } j = 0, 1$$

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- The out of sample R^2 is given by

$$R^2_{OS} = 1 - \frac{M\hat{S}FE_1}{M\hat{S}FE_0}$$

It gives the proportional reduction in the sample MSFE for the competing forecast with regard to the prevailing mean benchmark

Forecast Evaluation: Economic Value

- consider a mean-variance investor who allocates across equities and risk-free Treasury bills each month. At the end of month t, the investor faces the objective function

$$\arg\max_{w_{t+1|t}} \quad w_{t+1|t}\ \hat{r}_{M,t+1|t} - \frac{\gamma}{2} w_{t+1|t}^2\ \hat{\sigma}_{t+1|t}^2$$

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$$\bar{U}_j = \bar{r}_j - \frac{\gamma}{2}\hat{\sigma}_j^2 \quad \text{for } j = 0, 1$$

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- The average utility gain when the investor uses the competing forecast instead of the prevailing mean benchmark is

$$\Delta = \bar{U}_1 - \bar{U}_0$$

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Data

(1) Abbreviation	(2) Description	(3) Abbreviation	(4) Description
ABSACC	Absolute value of accruals	CURRAT	Current ratio
ACC	Accruals	DEPR	Depreciation to gross PP&E
AGE	Firm age	DOLVOL	Dollar trading volume
AGR	Asset growth	DROAQ	Change in quarterly return on assets
BETA1	Short-term beta	DROEQ	Change in quarterly return on equity
BETA1LAG	Short-term smoothed beta	EAR	Earnings announcement return
BETA3	Long-term beta	EGR	Book equity growth
BETA3LAG	Long-term smoothed beta	EP	Earnings to price
BM	Book to market	FERR	Earnings forecast error
CASH	Cash to assets	FP	Failure probability
CASHDEBT	Cash flow to debt	GPA	Gross profitability to assets
CASHPR	Cash productivity	GRLTD	Growth in long-term debt
CEIANN	Composite equity issuance, annual rebalancing	GRLTNOA	Growth in long-term net operating assets
CEIFY	Composite equity issuance, fiscal-year rebalancing	HERF	Industry sales concentration
CEIMO	Composite equity issuance, monthly rebalancing	HIRE	% change in employees
CFPIA	Industry-adjusted cash flow to price	IDIOVOL	Idiosyncratic return volatility
CFPJUN	Cash flow to price	ILLIQ	Illiquidity
CHATOIA	Industry-adjusted change in asset turnover	INDMOM12M	Twelve-month industry momentum
CHEMPIA	Industry-adjusted percent change in employees	INDMOM1M	One-month industry momentum
CHFEPS	Change in forecasted earnings per share	MAXRET	Maximum daily return
CHINV	Change in inventories	MOM12M	Twelve-month momentum
CHPMIA	Industry-adjusted change in profit margin	MOM1M	One-month momentum
CHTAX	% change in tax expense	MOM36M	36-month momentum
CINVEST	Corporate investment	MOM6M	Six-month momentum
CSUE	Composite earnings surprise	MS	Growth score

MVE	Market equity	ROE	Return on equity
NINCR	Number of quarters with consecutive earnings increase	ROEQ	Quarterly return on equity
NOA	Net operating assets	ROIC	Return on invested capital
NSIANN	Net share issuance, annual rebalancing	ROM	Return on market equity
NSIFY	Net share issuance, fiscal-year rebalancing	RSUP	Revenue surprise
NSIMO	Net share issuance, annual rebalancing	SALECASH	Sales to cash
OL	Operating leverage	SALEINV	Sales to inventories
OPERPROF	Operating profitability	SALEREC	Sales to receivables
ORGCAP	Organization capital to assets	SGR	Sales growth
OSCORE	O-score	SHR1	Short-term share issuance
PCHCURRAT	% change in current ratio	SHR5ANN	Long-term share issuance, annual rebalancing
PCHDEPR	% change in depreciation to gross PP&E	SHR5MO	Long-term share issuance, monthly rebalancing
PCHGMSALE	% change in gross margin minus % change in sales	SP	Sales to price
PCHQUICK	% change in quick ratio	SPI	Special items
PCHSALEINV	% change in sales minus % change in inventories	STDACC	Standard deviation of accruals
PCHSALEINVT	% change in sales to inventories	STDCF	Standard deviation of cash flows
PCHSALEREC	% change in sales minus % change in accounts receivable	STDTURN	Standard deviation of turnover
PCHSALESGM	% change in sales minus % change in SG&M	SUE	Standardized earnings surprise
PS	Fundamental score	TANG	Tangibility
QUICK	Quick ratio	TIBI	Taxable income to book income
RD	R&D expense to market	TURN	Total turnover
RETVOL	Return volatility	TURN3	Average turnover, three months
ROA	Return on assets	TURNL	Lagged total turnover
ROAQ	Quarterly return on assets	ZEROAVG	Average number of turnover-adjusted zero daily volume
ROAVOL	Volatility of return on assets	ZEROTOT	Total number of turnover-adjusted zero daily volume

Data

Table I

Summary Statistics

The table reports summary statistics for monthly anomaly portfolio returns for 100 anomalies. The sample period is 1970:01 to 2017:12. For each anomaly, we sort stocks into value-weighted decile portfolios according to the characteristic underlying the anomaly. The long-short anomaly portfolio goes long (short) the tenth (first) decile portfolio.

Number of anomalies	100
Fama and French (1993) three-factor model alpha	
Number of long-short anomaly portfolio returns with $\lvert t\text{-stat.}\rvert \geq 1.645$	75
Number of long-short anomaly portfolio returns with $\lvert t\text{-stat.}\rvert \geq 1.96$	71
Number of long-short anomaly portfolio returns with $\lvert t\text{-stat.}\rvert \geq 2.58$	56
Number of long-short anomaly portfolio returns with $\lvert t\text{-stat.}\rvert \geq 3$	49
Average correlation across anomaly decile rankings	0.05
Average correlation across monthly anomaly excess returns	
Long leg	0.76
Short leg	0.82
Long-short	0.08
Long-leg anomaly portfolio excess returns	
Average of sample means	0.71%
Average of sample standard deviations	5.16%
Short-leg anomaly portfolio excess returns	
Average of sample means	0.33%
Average of sample standard deviations	6.20%
Long-short anomaly portfolio returns	
Average of sample means	0.38%
Average of sample standard deviations	4.37%

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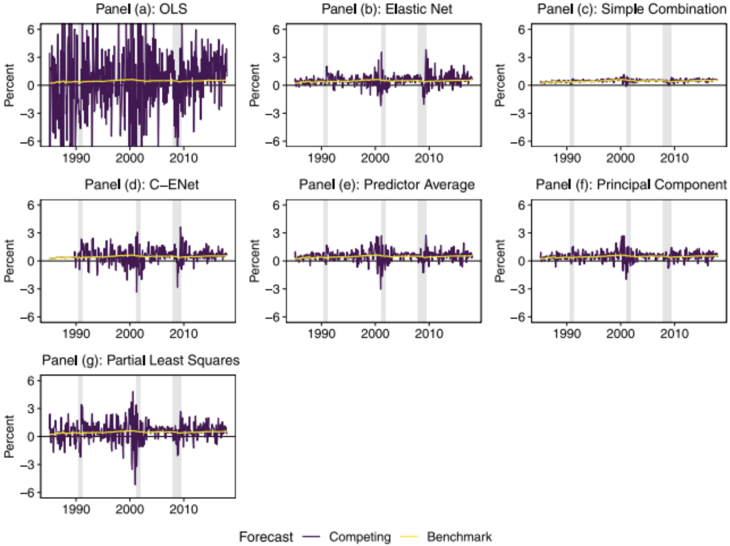
Results: Forecast Accuracy



Results: Forecast Accuracy

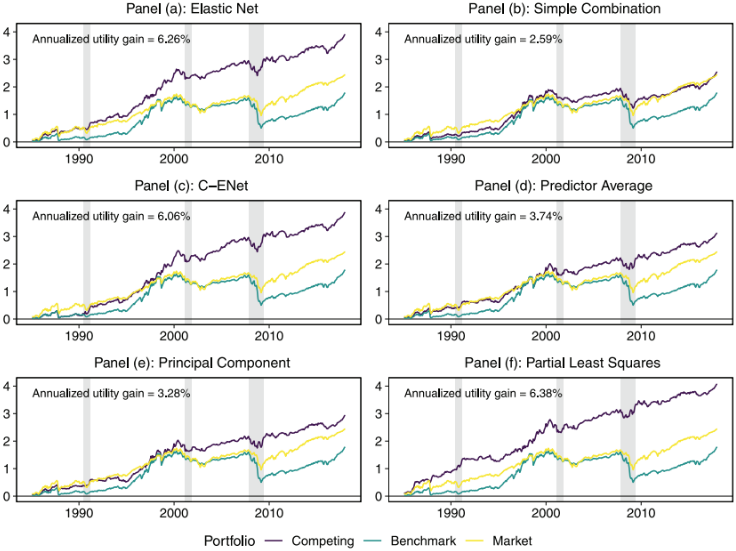
Table II

R^2_{OS} Statistics

The table reports Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OS}) statistics in percent for market excess return forecasts based on 100 anomaly portfolio returns. The out-of-sample period is 1985:01 to 2017:12. The OLS (ENet) forecast is based on ordinary least squares (elastic net) estimation of a multiple predictive regression that includes all 100 of the anomaly portfolio returns. Combine is the arithmetic mean of univariate predictive regression forecasts based on the 100 individual anomaly portfolio returns (considered in turn). C-ENet is the arithmetic mean of the univariate predictive regression forecasts selected by the elastic net in a Granger and Ramanathan (1984) regression. Avg is a univariate predictive regression forecast based on the cross-sectional average of the 100 anomaly portfolio returns. PC (PLS) is a univariate predictive regression forecast based on the first principal component (target-relevant factor) extracted from the 100 anomaly portfolio returns. Based on the Clark and West (2007) test, *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, for the positive R^2_{OS} statistics.

(1) Anomaly Portfolio	(2) OLS	(3) ENet	(4) Combine	(5) C-ENet	(6) Avg	(7) PC	(8) PLS
Long-short return	−2,513.86	2.03**	0.89***	2.81***	1.89**	1.25**	2.06***
Long-leg excess return	−344,960.22	−0.90	0.29	−0.68	0.26	0.24	0.41
Short-leg excess return	−13,284.68	1.81*	0.72*	0.39*	0.75*	0.74*	0.84*

Results: Economic Value



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Conclusion

- A representative group of 100 long-short anomaly portfolio returns from the cross-sectional literature contains valuable information for predicting the market excess return on an out-of-sample basis, provided that we use forecasting strategies that guard against overfitting the data