Fundamental Analysis and Mean-Variance Optimal Portfolios

Lyle M R , Yohn T L .

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解读者：屠雪永

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Outline

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- Research design
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  - Fundamental Analysis and Stock Returns
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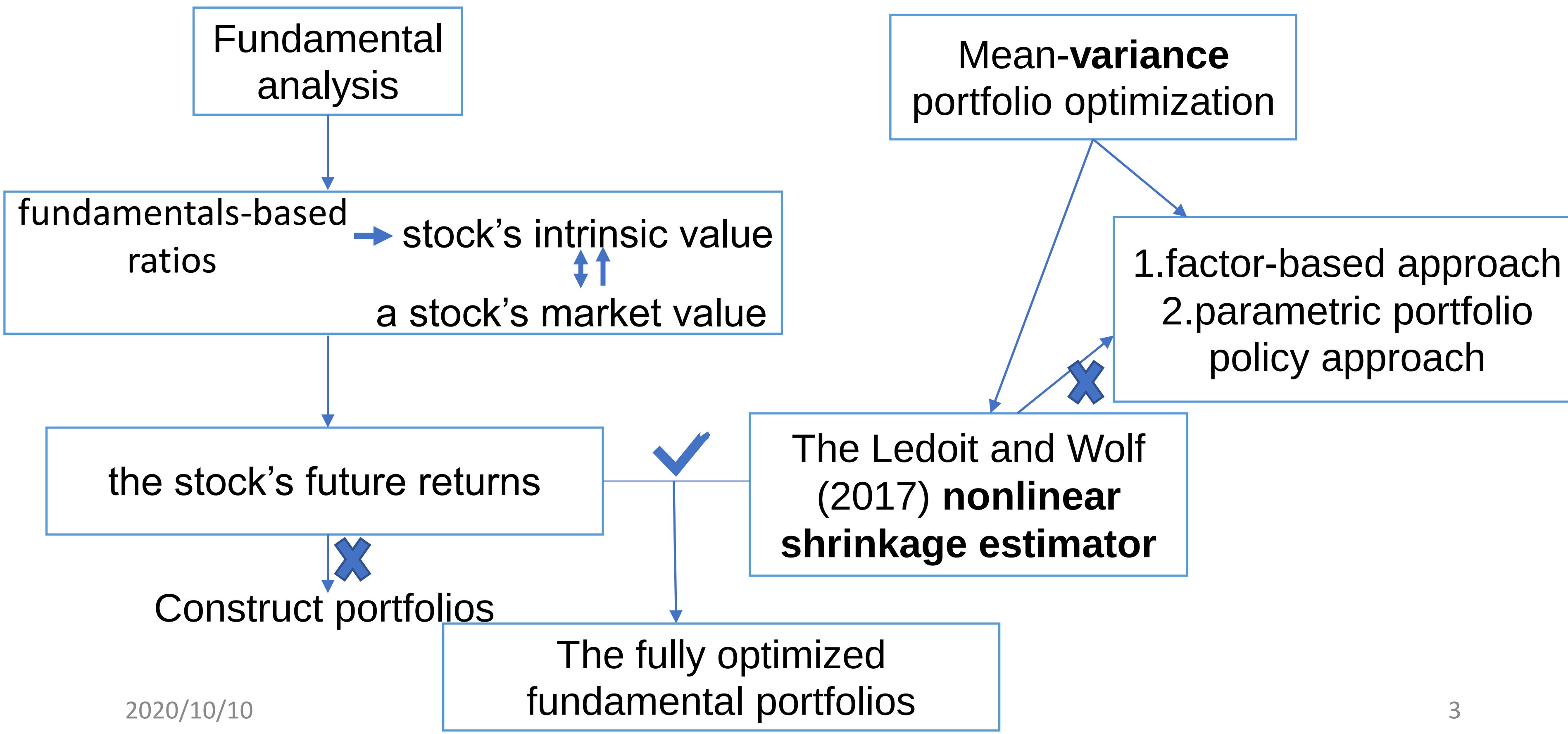
  - Related comparisons and robust tests
- Conclusion

1.Introduction

1.1. Motivation

- We integrate fundamental analysis with mean-variance portfolio optimization to form fully optimized fundamental portfolios*(FOP)*.



1.Introduction

1.2. Framework

Prior Literature an Extensions

- Fundamental Analysis and Extreme Decile/Break Point Portfolios
- Optimal Portfolios
  - ① Mean-Variance
  - ② Factor-Based Approach
  - ③ Parametric Portfolio Policies
  - ④ **Large Dimension Covariance Estimation**
  - ⑤ Nested Portfolios for Performance Attribution
    - a. **"Fully" Optimized Portfolios**
    - b. Covariance-Only Portfolios
    - c. Expected Returns-Only Portfolios
    - d. Naive Equal-Weighted Portfolios

$$w = \frac{\Sigma^{-1}\mu}{e^T\Sigma^{-1}\mu}.$$

Fundamental Analysis and Stock Returns

Data and Estimation

Empirical Results

Conclusion

1.Introduction

1.3. Contribution

- This study extends the academic research on fundamental analysis and portfolio optimization:
    - Firstly, using a large sample, incorporate fundamentals-based expected stock returns and a covariance matrix.
    - Secondly, gains from the fully optimized fundamental portfolios over portfolios in the prior optimization literature.
    - Thirdly, our approach to portfolio optimization provides practical benefits with respect to implementation.

2. Research design

2.1. Fundamental Analysis and Extreme Decile/Break Point Portfolios

The portfolio weight for stock i with a fundamental signal S_i would be:

$$w_i = \begin{cases} \frac{1}{N^{HD}}, & S_i \in D^{HD} \\ 0, & S_i \notin \{D^{HD}, D^{LD}\} \\ -\frac{1}{N^{LD}}, & S_i \in D^{LD} \end{cases}$$

where D^{HD} (D^{LD}) represents the upper (lower) decile of the signal and N^{HD} (N^{LD}) represents the number of stocks in the respective decile.

2. Research design

2.2. Optimal Portfolios

The cross-section of stock returns in matrix form, r,as follows:

$$r = \mu + \sqrt{\Sigma}\epsilon, \tag{1}$$

$$\mu = (\mu_{1,t}, \mu_{2,t}, \ldots \mu_{N,t})^T, \tag{2}$$

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \ldots & \sigma_{1N} \\ \sigma_{12} & \sigma_{22} & \ldots & \sigma_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1N} & \sigma_{2N} & \ldots & \sigma_{NN} \end{bmatrix}, \tag{3}$$

$$\epsilon = (\epsilon_{1,t+1}, \epsilon_{2,t+1}, \ldots, \epsilon_{N,t+1})^T. \tag{4}$$

The portfolio's return: $r_{p,t+1} = w^T r$ where $w = (w_1, w_2, \ldots, w_N)^T$

The portfolio's expected return: $E_t[r_{p,t+1}] = w^T \mu$

The portfolio's variance: $E_t[r^2_{p,t+1}] - E_t[r_{p,t+1}]^2 = w^T \Sigma w.$

2. Research design

2.2.1. Mean-Variance

A Markowitz (1952) mean-variance optimal stock portfolio:

$$\max_{w} w^T \mu, \tag{5}$$

$$\text{s.t. } w^T \Sigma w = \Sigma_p, \tag{6}$$

$$w^T e = 1, \tag{7}$$

Maximizing the expected portfolio return per unit of portfolio volatility (i.e., **maximum Sharpe ratio**) results in the following optimal portfolio policy:

$$w = \frac{\Sigma^{-1}\mu}{e^T \Sigma^{-1}\mu}. \tag{8}$$

The difficulties: unreliable expected return estimates and error in the estimation of the covariance matrix.

2. Research design

2.2.2. Factor-Based Approach(FB)

This approach **reduces the dimension** of the covariance matrix by assuming that returns have a linear “factor structure” :

$$\mu_{FB} = \alpha + F^T \beta, \tag{9}$$

$$\Sigma_{FB} = \beta^T \Sigma_F \beta + \Lambda, \tag{10}$$

where α is a constant,

F is a $K \times 1$ vector of expected returns on the factor portfolios,

and β is a $K \times N$ matrix of factor sensitivities ,

Σ_F is the covariance matrix of factor portfolios

and Λ is a diagonal matrix of idiosyncratic variances.

$$w_{FB} = \frac{\Sigma_{FB}^{-1} \mu_{FB}}{e^T \Sigma_{FB}^{-1} \mu_{FB}}. \tag{11}$$

$$N(N+1)/2 \longrightarrow N + K(K+1)/2$$

2. Research design

2.2.3. Parametric Portfolio Policies (PPP)

The characteristics-based parametric portfolio policy approach

$$\omega_{ppp} = \bar{\omega} + X^{T}\theta \tag{12}$$

$\bar{\omega}$ is a $N \times 1$ vector of weights for some benchmark portfolio,

θ is a $M \times 1$ vector of coefficients that need to be estimated,

X is a $M \times N$ vector of standardized firm characteristics divided by the number of firms (*N*) in the cross-section.

$$\max_{\theta} \frac{1}{t} \sum_{j=0}^{t-1} \frac{(1 + w_{PPP}^{T} r_j)^{1-\gamma}}{1-\gamma}, \tag{13}$$

$$\text{s.t. } w_{PPP} = \bar{w} + \theta^{T} X, \tag{14}$$

$$e^{T} w_{PPP} = 1, \tag{15}$$

$$e^{T} \theta^{T} X = 0, \tag{16}$$

2. Research design

2.3. Large Dimension Covariance Estimation

Ledoit and Wolf (2017) develop a nonlinear shrinkage estimator for covariance matrix estimation which can be readily applied to mean-variance portfolio optimization.

2.4. Nested Portfolios for Performance Attribution

Any **performance gains** from the optimized fundamental portfolios over naive equal-weighted portfolios are attributable to the use of the fundamentals-based **expected returns model, the covariance matrix, or both.**

2. Research design

2.4.1. "Fully" Optimized Portfolios (FOP)

$$w_{FOP} = \frac{\Sigma^{-1}\mu}{e^T\Sigma^{-1}\mu}. \tag{17}$$

2.4.2. Covariance-Only Portfolios (COV)

$$w_{COV} = \frac{\Sigma^{-1}e}{e^T\Sigma^{-1}e}. \tag{18}$$

2.4.3. Expected Returns-Only Portfolios (ER)

$$w_{ER} = \frac{\mu}{e^T\mu}. \tag{19}$$

2.4.4. Naive Equal-Weighted Portfolios (EW)

$$w_{EW} = \frac{1}{N}e. \tag{20}$$

$$\mu = c \times e \text{ and } \Sigma = C \times I$$

2. Research design

2.5. Fundamental Analysis and Stock Returns

Assume that the difference between the market value and intrinsic value for stock i, $M_{i,t} - V_{i,t}$, follows an $AR(1)$ process, with an unconditional mean of zero:

$$M_{i,t+1} - V_{i,t+1} = \omega_i(M_{i,t} - V_{i,t}) + \epsilon_{i,t+1}. \tag{21}$$

$\omega_i \in (0,1)$ represents a persistence parameter, and $\epsilon_{i,t+1}$is a mean-zero noise term with bounded variance.

$$V_{i,t} = \sum_{j=1}^{\infty} \mathbb{E}_t^F[R_i^{-j} D_{i,t+j}]$$

$$\mathbb{E}_t^F[V_{i,t+1} + D_{i,t+1}] = R_i V_{i,t}$$, where $R_i > 1$

$$\frac{M_{i,t+1} + D_{i,t+1}}{M_{i,t}} = \underbrace{\frac{V_{i,t}}{M_{i,t}} R_i + \omega_i\left(1 - \frac{V_{i,t}}{M_{i,t}}\right)}_{\text{Expected Return}} + \underbrace{\frac{(V_{i,t+1} + D_{i,t+1}) - R_i V_{i,t}}{M_{i,t}}}_{\text{Fundamentals Shock}} + \underbrace{\frac{\epsilon_{i,t+1}}{M_{i,t}}}_{\text{Convergence Shock}} . \tag{22}$$

2. Research design

2.5. Fundamental Analysis and Stock Returns

$$R_{i,t+1} \equiv \frac{M_{i,t+1} + D_{i,t+1}}{M_{i,t}} = \omega_i + \frac{V_{i,t}}{M_{i,t}}(R_i - \omega_i) + \Omega_{i,t}\xi_{i,t+1}, \tag{23}$$

$$\begin{tikzcd}
V_{i,t} \arrow[rr] \arrow[dr] & & B_{i,t} & \\
& x^{a}_{i,t+j} \arrow[ur] \arrow[dr] & & x_{i,t} \\
& & x_{i,t+1} \arrow[ur] \arrow[r] \arrow[dr] & \Delta NOA_{i,t} \\
& & & \Delta FIN_{i,t}
\end{tikzcd}$$

$$R_{i,t+1} = A_{i,0} + A_{i,1}\frac{1}{M_{i,t}} + A_{i,2}\frac{B_{i,t}}{M_{i,t}} + A_{i,3}\frac{x_{i,t}}{M_{i,t}} + A_{i,4}\frac{\Delta NOA_{i,t}}{M_{i,t}} + A_{i,5}\frac{\Delta FIN_{i,t}}{M_{i,t}} + \Omega_{i,t}\xi_{i,t+1}. \tag{29}$$

Market value $M_{i,t}$, book value $B_{i,t}$, current earnings, $x_{i,t}$,
growth in net operating assets, $\Delta NOA_{i,t}$,and growth in financing, $\Delta FIN_{i,t}$

3. Empirical result

3.1.1. Data

Data sources: CRSP , Compustat and Ken French's data library

Sample time period:1976-2017.

Windows width: rolling five-year periods of historical monthly data.

Data processing :

remove stocks below one dollar ,a negative book value, and less than five years of historical stock return data,

remove financial and regulated firms,

all expected return estimates winsorized at the 1% and 99% levels.

3. Empirical result

3.1.2. Model Estimation for Mean-Variance Optimization

Estimating the coefficients {A0, A1, A2, A3, A4, A5} :

we collect five years of historical data to by regressing one month-ahead stock returns on the fundamental variables.

we update predictor variables $\frac{1}{M_t}$, $\frac{B_t}{M_t}$, $\frac{x_t}{M_t}$, $\frac{\Delta NOA_{i,t}}{M_{i,t}}$ and $\frac{\Delta FIN_{i,t}}{M_{i,t}}$ quarterly.

3. Empirical result

3.1.2. Model Estimation for Mean-Variance Optimization

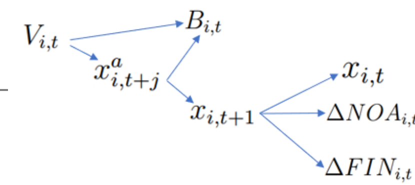


Table 1: Regression Tests

(a) Panel A: Quarterly Earnings Regressions

dependent variable: $\frac{X_{t+1}}{M_t}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\frac{X_t}{M_t}$	0.380***	0.368***	0.406***	0.387***	0.364***	0.341***	0.330***
	(6.227)	(6.045)	(7.081)	(6.714)	(6.586)	(6.614)	(6.522)
$\frac{\Delta FIN_t}{M_t}$		0.057***		0.052***	0.049***	0.043***	0.042***
		(9.576)		(9.561)	(9.239)	(11.835)	(11.513)
$\frac{\Delta NOA_t}{M_t}$			-0.030***	-0.020***	-0.020***	-0.024***	-0.024***
			(-5.672)	(-3.895)	(-4.358)	(-4.241)	(-4.498)
$\frac{1}{M_t}$					-0.127***		-0.082***
					(-7.128)		(-4.616)
$\frac{B_t}{M_t}$						-0.031***	-0.029***
						(-5.542)	(-4.888)
# Obs.	531,565	531,565	531,565	531,565	531,565	531,565	531,565
R^2	0.186	0.194	0.189	0.195	0.21	0.244	0.25

- Earnings, book value, and growth are informative about future earnings

3. Empirical result

3.1.2. Model Estimation for Mean-Variance Optimization

(b) Panel B: Monthly Return Regressions

	dependent variable: $100 \times R_{t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
							0.594***
μ_t							(12.828)
$\frac{1}{M_t}$	0.412*					0.462*	
	(1.676)					(1.787)	
$\frac{B_t}{M_t}$		0.783***				0.548**	
		(3.314)				(2.091)	
$\frac{X_t}{M_t}$			1.662***			1.815***	
			(6.981)			(8.647)	
$\frac{\Delta FIN_t}{M_t}$				0.894***		0.390***	
				(9.796)		(4.233)	
$\frac{\Delta NOA_t}{M_t}$					-0.786***	-0.900***	
					(-7.699)	(-8.987)	
# Obs.	861,474	861,474	861,474	861,474	861,474	861,474	861,474
$100 \times R^2$	0.007	0.027	0.123	0.035	0.027	0.208	0.244

- The fundamentals-based model is a strong predictor of future stock returns.

3. Empirical result

3.2.1. Optimal Fundamental Portfolios Performance

Table 2: Unconstrained Portfolio Performance

$$SR = \frac{\bar{R}_{P,t+1} - \bar{R}_F}{\sqrt{\sigma^2_{P,t+1}}},$$

(a) Panel A: Portfolio Summary Statistics

		Long-Short			Long-Only		
Portfolio:	EW	COV	ER	FOP	COV	ER	FOP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean	1.275	1.148	1.763	3.850	1.011	1.745	1.920
Std.	5.310	2.984	5.605	6.732	3.376	5.638	4.307
SR	0.176	0.271	0.253	0.524	0.198	0.249	0.367

(b) Panel B: Sharpe Ratio Differences

Portfolios:	COV-EW	ER-EW	ER-COV	FOP-COV	FOP-ER	FOP-EW
	(1)	(2)	(3)	(4)	(5)	(6)
Long-Short	0.095***	0.077***	-0.018	0.253***	0.271***	0.348***
Long-Only	0.022	0.073***	0.051*	0.169***	0.118***	0.191***

- Under unconstrained situation , the FOP portfolios generate the highest future stock returns.

3. Empirical result

3.2.1. Optimal Fundamental Portfolios Performance

Table 3: Constrained Portfolio Performance

-2.5%~2.5%   0~2.5%

(a) Panel A: Portfolio Summary Statistics

		Long-Short			Long-Only		
Portfolio:	EW	COV	ER	FOP	COV	ER	FOP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean	1.275	1.148	1.773	3.681	1.017	1.746	1.876
Std.	5.310	2.984	5.615	4.951	3.373	5.639	4.114
SR	0.176	0.271	0.255	0.684	0.200	0.249	0.373

(b) Panel B: Sharpe Ratio Differences

Portfolios:	COV-EW	ER-EW	ER-COV	FOP-COV	FOP-ER	FOP-EW
	(1)	(2)	(3)	(4)	(5)	(6)
Long-Short	0.095***	0.079***	-0.016	0.413***	0.429***	0.508***
Long-Only	0.024	0.073***	0.049*	0.173***	0.124***	0.197***

- Under constrained situation ,the FOP portfolios generate the highest future stock returns.

3. Empirical result

3.2.2. Alternative Approaches to Portfolio Construction

Table 4: Alternative Portfolio Optimization

(a) Panel A: Portfolio Summary Statistics

	Long-Short				Long-Only			
	Unconstrained		Constrained		Unconstrained		Constrained	
Portfolio:	FB	PPP	FB	PPP	FB	PPP	FB	PPP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean	1.198	2.416	1.190	1.259	1.195	1.254	1.195	1.254
Std.	4.372	5.408	4.361	5.192	4.363	5.193	4.363	5.193
SR	0.198	0.384	0.195	0.177	0.197	0.178	0.196	0.177

(b) Panel B: Sharpe Ratio Differences

Portfolios:		FB-EW	PPP-EW	FB-FOP	PPP-FOP
		(1)	(2)	(3)	(4)
Long-Short	Unconstrained	0.022***	0.208***	-0.328***	-0.140*
	Constrained	0.019**	0.001**	-0.172***	-0.190***
Long-Only	Unconstrained	0.021***	0.002	-0.488***	-0.508***
	Constrained	0.020***	0.001	-0.177***	-0.197***

- The FOP portfolios dominate the portfolio performance of FB and PPP approaches.

3. Empirical result

3.2.2. Alternative Approaches to Portfolio Construction

Table 5: Extreme Decile Portfolios

(a) Panel A: Portfolio Summary Statistics

	Long-Short					Long-Only				
Portfolio:	EWED	VWED	COV	ER	FOP	EWED	VWED	COV	ER	FOP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mean	2.360	1.473	2.170	2.599	2.521	2.619	2.078	2.352	2.716	2.593
Std.	3.487	5.810	2.796	3.710	3.053	6.730	7.429	4.922	6.782	5.104
SR	0.580	0.195	0.655	0.609	0.715	0.339	0.234	0.409	0.351	0.442

(b) Panel B: Sharpe Ratio Differences

Portfolios:	EWED-COV	EWED-ER	EWED-FOP	VWED-COV	VWED-ER	VWED-FOP
	(1)	(2)	(3)	(4)	(5)	(6)
Long-Short	-0.075*	-0.029***	-0.135***	-0.460***	-0.414***	-0.520***
Long-Only	-0.070***	-0.012***	-0.103***	-0.175***	-0.117***	-0.208***

- The FOP portfolios generate the highest future stock returns, EWED and VWED portfolios significantly underperform relative to others.

3. Empirical result

3.2.3. Alphas and Information Ratios

Table 6: Alphas and Information Ratios

$$R_{FOP,t+1} = \alpha + \beta \times R_{Bench,t+1} + \epsilon_{t+1},$$

(a) Panel A: α's and IR's relative to alternative fundamentals-based portfolios

	Long-Short		Long-Only	
Benchmark	α	IR	α	IR
FB	2.934***	0.709	0.895***	0.756
PPP	3.050***	0.722	1.022***	0.738
EWED	0.996***	0.483	0.800***	0.815
VWED	2.240***	0.786	1.494***	0.593

The Information ratio as α divided by the standard deviation of the residual.

$$R_{FOP,t+1} = \alpha + \sum_{j=1}^{m} \beta_j \times f_{j,t+1} + \epsilon_{t+1},$$

(b) Panel B: α's and IR's relative to asset pricing factors

	Long-Short		Long-Only	
Benchmark	α	IR	α	IR
CAPM	3.158***	0.715	1.179***	0.535
FF3	3.068***	0.715	1.071***	0.667
FF4	3.059***	0.712	1.138***	0.673
FF5	3.011***	0.701	0.988***	0.672

- None of the benchmark portfolios replicate the returns of the FOP portfolios..

3. Empirical result

3.2.4. Portfolio Performance Over Time

Table 7: Portfolio Performance Over Time

			Long-Short			Long-Only		
Portfolio:		EW	COV	ER	FOP	COV	ER	FOP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
1981-1987	Mean	1.478	1.930	2.074	6.265	1.589	2.018	2.536
	Std.	5.846	3.715	6.089	6.294	4.187	6.065	4.891
	SR	0.130	0.325	0.222	0.879	0.209	0.214	0.371
1988-1997	Mean	1.388	1.231	2.120	4.886	0.977	2.005	2.083
	Std.	3.957	2.134	4.171	3.664	2.620	4.132	2.980
	SR	0.238	0.363	0.400	1.217	0.200	0.376	0.542
1998-2007	Mean	1.207	0.888	1.792	2.724	0.856	1.727	1.694
	Std.	5.625	2.986	6.187	4.084	3.033	6.170	3.701
	SR	0.163	0.199	0.242	0.591	0.185	0.232	0.377
2008-2017	Mean	1.089	0.779	1.198	1.624	0.816	1.315	1.390
	Std.	5.834	3.080	5.968	4.728	3.723	6.127	4.822
	SR	0.182	0.245	0.197	0.338	0.213	0.211	0.283

- The gains from the FOP portfolios are not driven by a particular time period. And there has been a **decline** over time in the returns.

3. Empirical result

3.2.5. Portfolio Performance and Implementation Issues

Table 8: Performance by Size

			Long - Short			Long Only		
Portfolio:		EW	COV	ER	FOP	COV	ER	FOP
Size Group		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Top 1,000	Mean	1.192	1.082	1.415	2.901	1.118	1.423	1.586
	Std.	5.148	3.045	5.387	4.399	3.302	5.399	3.848
	SR	0.165	0.245	0.200	$\boxed{0.592}$	0.236	0.201	$\boxed{0.325}$
Top 500	Mean	1.137	1.100	1.285	2.189	1.140	1.290	1.458
	Std.	4.838	3.194	5.029	3.978	3.426	5.029	3.791
	SR	0.165	0.239	0.188	$\boxed{0.471}$	0.234	0.189	$\boxed{0.296}$
Top 200	Mean	1.085	1.073	1.184	1.576	1.088	1.187	1.269
	Std.	4.542	3.543	4.675	4.059	3.551	4.668	3.852
	SR	0.164	0.208	0.180	$\boxed{0.306}$	0.211	0.181	$\boxed{0.241}$
Top 100	Mean	1.068	1.031	1.156	1.248	1.078	1.156	1.189
	Std.	4.355	3.652	4.415	3.816	3.650	4.423	3.841
	SR	0.167	0.190	0.185	$\boxed{0.238}$	0.203	0.184	$\boxed{0.221}$

- Returns and SRs **decline** as the investment set is limited to larger stocks. But the FOP portfolios dominate within each size group.

3. Empirical result

3.2.5. Portfolio Performance and Implementation Issues

Table 9: Leverage, Exposure and Transaction Costs

Protfolio		EW	Long-Short COV	Long-Short ER	Long-Short FOP	Long-Only COV	Long-Only ER	Long-Only FOP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Portfolio Weights								
Long-side:	$\omega_L = \sum_{i=0}^{N_t} \lvert\omega_i\rvert \times I(\omega_i \geq 0)$	1.000	1.545	1.049	$\boxed{2.580}$	1.000	1.000	1.000
Short-side:	$\omega_S = \sum_{i=0}^{N_t} \lvert\omega_i\rvert \times I(\omega_i < 0)$	0.000	0.545	0.049	$\boxed{1.580}$	0.000	0.000	0.000
Net exposure:	$\omega_L - \omega_S = \sum_{i=0}^{N_t} \omega_i$	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Gross exposure:	$\omega_L + \omega_S = \sum_{i=0}^{N_t} \lvert\omega_i\rvert$	1.000	2.090	1.099	$\boxed{4.159}$	1.000	1.000	1.000
Panel B: Factor Sensitivities								
Sensitivity to Market		$\boxed{1.021}$	$\boxed{0.700}$	1.045	$\boxed{0.643}$	0.530	1.041	0.560
Sensitivity to HML		0.105	0.182	0.128	0.107	0.161	0.099	0.113
Sensitivity to SMB		0.734	0.520	0.775	0.372	0.367	0.752	0.248
Sensitivity to RMW		-0.002	0.111	-0.050	0.151	0.081	-0.054	0.210
Sensitivity to CMA		0.067	0.116	0.027	0.216	0.071	0.045	0.215

- The FOP portfolios have significantly higher gross exposure than the other portfolios .
- Utilizing information in the covariance matrix (i.e., the COV and FOP portfolios) tend to have lower β's than the EW or ER portfolios.

3. Empirical result

3.2.5. Portfolio Performance and Implementation Issues

Table 9: Leverage, Exposure and Transaction Costs

Protfolio	EW	Long-Short			Long-Only		
		COV	ER	FOP	COV	ER	FOP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: Post-Transaction Cost Performance							
Mean	1.260	1.002	1.400	1.745	0.889	1.441	1.263
Std.	5.319	3.003	5.593	4.768	3.396	5.635	4.129
SR	0.173	0.221	0.190	$\boxed{0.295}$	0.162	0.196	$\boxed{0.224}$

- The FOP portfolios outperform the other portfolios in terms of the SR, even after transactions costs.

4. Conclusion

- Firstly, The FOP portfolios produce large out-of-sample factor alphas with high Sharpe ratios, outperform equal-weighted and value-weighted portfolios of stocks in the extreme decile of expected returns.
- Secondly, They outperform the factor-based and parametric portfolio policy approaches.
- Finally, the gains from the FOP portfolios are robust when taking time, firm size and transactions costs into consideration.

5. Consideration

- 1. It will be more convincing that if the fundamental signals are replaced by Fama-French five factors, the models still have better performance.
- 2. We can use machine learning methods to predict future returns instead of fundamental analysis in this article.