Advanced Investment Analytics

Jantz

The Jantz Analytics Platform

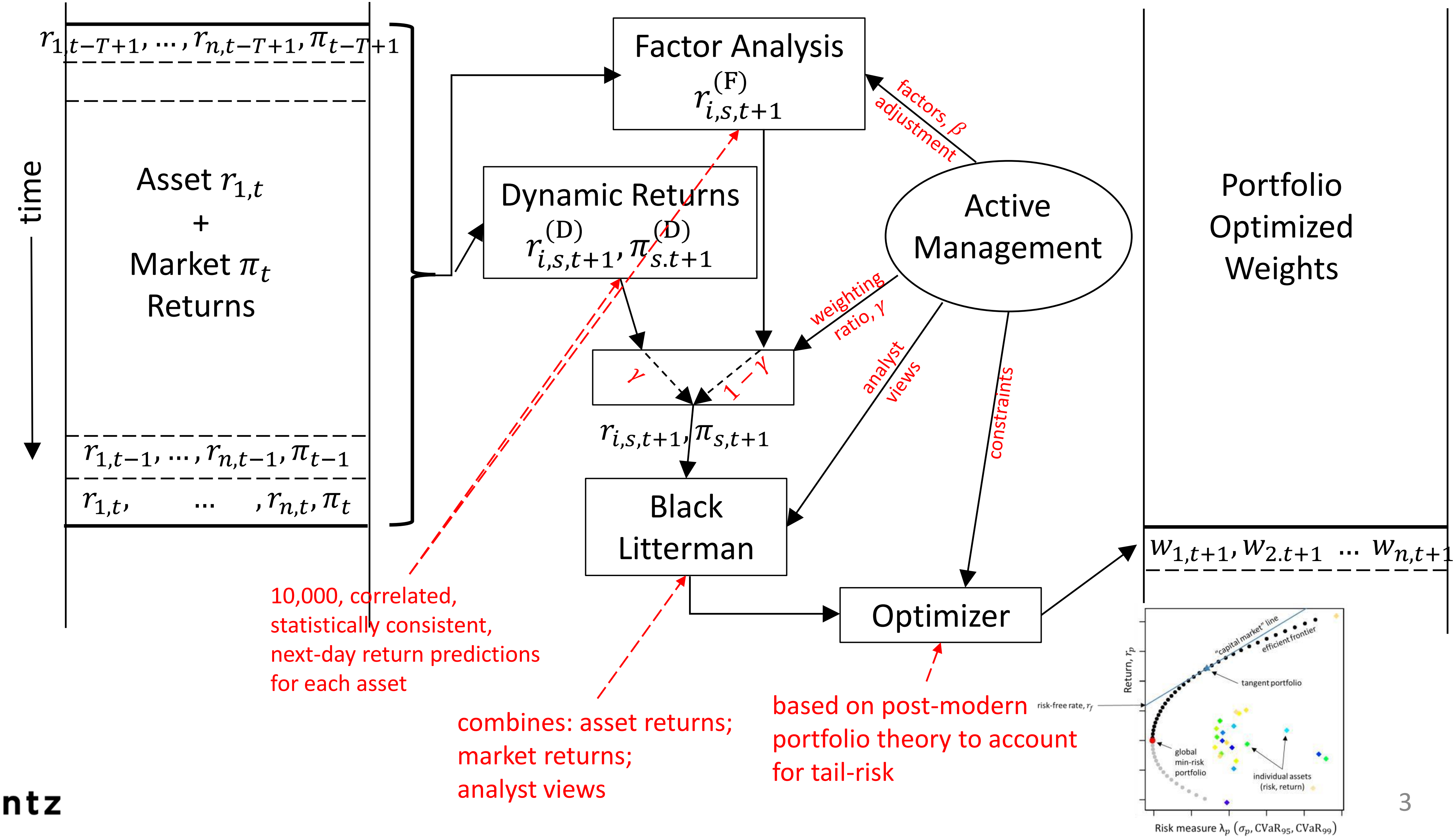
An investment platform featuring

1. risk-return sophisticated portfolios, including
   - optimization based upon post-modern portfolio theory
   - dynamic (look ahead) portfolio optimization
   - factor analysis-based optimization
   - Black-Litterman implementation of market and management views
   - the ability to maximize overall ESG rating along with traditional return
   - daily backtesting

2. a suite of risk analytics/tools
   - performance ratios
   - incremental and component value-at-risk
   - statistical factor analysis
   - performance attribute constraints
   - early warning systems

3. derivative pricing based upon arbitrage-free, dynamic asset pricing theory, including
   - improved asset pricing
   - ESG derivative pricing
   - future volatility forecasting based on
     – VIX-like implied volatility
     – “intrinsic time” volatility

Optimization featuring Dynamic Return Forecasting and Active Management



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Dynamic Return Forecast

asset return

random shocks

ARMA $r_{t+1} = f(r_t) + h(a_{t+1}, a_t)$

GARCH model

$a_{t+1} = \sigma_{t+1} \epsilon_{t+1}$

$\sigma_{t+1}^2 = g(\sigma_t^2, a_t^2)$

Captures volatility clustering, skewness, & heavy-tails

$f(), h(), g()$ comprise the systematic component of the model for each asset

Jantz Analytics platform pays attention to the random process capturing correlated response of assets to shocks

1. Determine an appropriate multivariate model $\mathcal{E}$ for the random process ϵ_t
2. Fit the ARMA-GARCH-$\mathcal{E}$ model to asset return data
3. From the fitted $\mathcal{E}$ model generate 10,000 scenarios (Basel II accord) of $\epsilon_{s,t+1}$, $s = 1, \dots, 10{,}000$ for each asset
4. Combine the systematic components with the $\epsilon_{s,t+1}$ scenarios to predict 10,000 return scenarios $r_{s,t+1}^{(\mathrm{D})}$ for each asset
5. Combine the $r_{s,t+1}^{(\mathrm{D})}$ scenarios with the scenarios generated by the factor model $r_{s,t+1}^{(\mathrm{F})}$

$$r_{s,t+1} = \gamma r_{s,t+1}^{(\mathrm{D})} + (1-\gamma) r_{s,t+1}^{(\mathrm{F})}$$

6. Pass $\{r_{s,t+1}\}$ to optimizer to generate weights for next day

Factor Analysis

Universe of Factors g_{it}

exogenous: indices, company performance measures

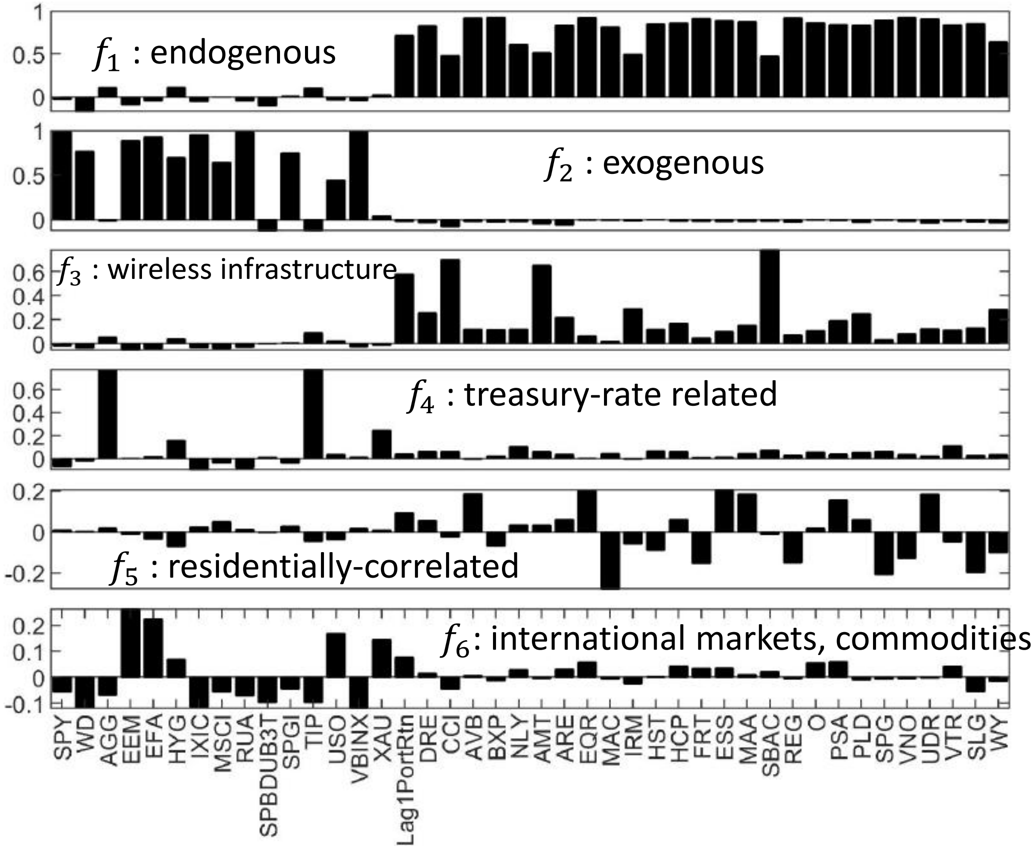
endogenous: past returns

Test universe for k factors (MSCI Barra)

Factor model: $\boldsymbol{r}_t = \boldsymbol{\mu} + \sum_{j=1}^{k} \beta_j f_{jt} + \boldsymbol{\epsilon}_t$

- asset return: $\boldsymbol{r}_t$
- mean return: $\boldsymbol{\mu}$
- loadings: β_j
- factors: f_{jt}
- unexplained return: $\boldsymbol{\epsilon}_t$

$$f_{jt} = \sum_{i=1} a_{ji} g_{it}$$



Select k specific factors (Fama-French)

$$f_{jt} = g_{jt}$$

$$\boldsymbol{r}_t = \beta_0 + \beta_1 \mathrm{EP}_t + \beta_2 \mathrm{BP}_t + \beta_3 \mathrm{CP}_t + \beta_4 \mathrm{SP}_t + \beta_5 \mathrm{REP}_t + \beta_6 \mathrm{RBP}_t + \beta_7 \mathrm{RCP}_t + \beta_8 \mathrm{RSP}_t + \beta_9 \mathrm{CTEF}_t + \beta_{10} \mathrm{PM}_t + \beta_{11} \mathrm{FG}_t + \boldsymbol{\epsilon}_t$$

- EP: earnings / price
- BP: book value / price
- CP: cash flow / price
- SP: sales / price
- REP: current EP/5yr av EP
- RBP: current BP/5yr av BP
- RCP: current CP/5yr av CP
- RSP: current SP/5yr av SP
- CTEF: consensus earnings forecast
- PM: price momentum
- FG: CNN fear & greed index

factor loadings → factor loadings →

risk analysis: determine return and risk sensitivity to factors

optimization: to generate predictive returns

Factor Analysis Return Forecast (cont'd)

Existing methods focus on the systematic component of factor model

Factor model $\boldsymbol{r}_{t+1} = \boldsymbol{\mu} + \sum_{j=1}^{k} \beta_j f_{jt} + \boldsymbol{\epsilon}_{t+1}$

Jantz model does not ignore the stochastic component

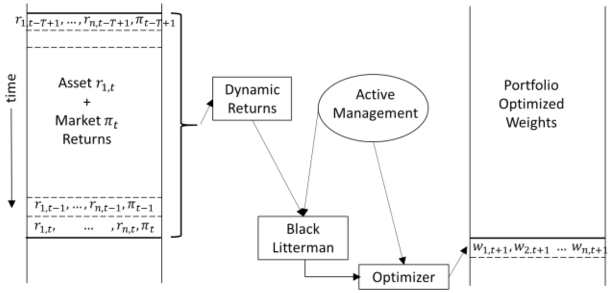
1. Perform a time-series analysis of the correlation structure between the $\boldsymbol{\epsilon}_t$ of each asset
2. From the correlation structure generate 10,000 scenarios of $\boldsymbol{\epsilon}_{s,t+1}$, $s = 1, \dots, 10{,}000$ for each asset
3. Combine the systematic component $\sum_{j=1}^{k} \beta_j f_{jt}$ with the $\boldsymbol{\epsilon}_{s,t+1}$ scenarios to predict 10,000 return scenarios $r_{s,t+1}^{(\mathrm{F})}$ for each asset
4. Combine the $r_{s,t+1}^{(\mathrm{F})}$ scenarios with the scenarios generated by the existing dynamic module $r_{s,t+1}^{(\mathrm{D})}$

$$r_{s,t+1} = \gamma r_{s,t+1}^{(\mathrm{D})} + (1-\gamma) r_{s,t+1}^{(\mathrm{F})}$$

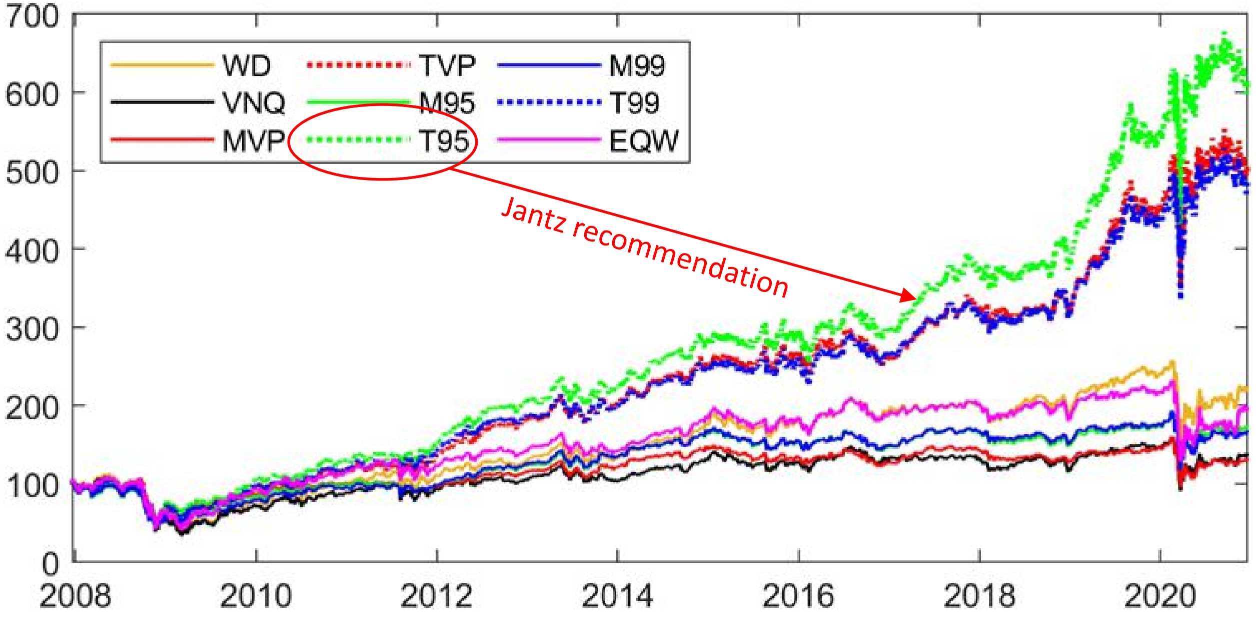
5. Pass $\{r_{s,t+1}\}$ to optimizer to generate weights for next day

Dynamic vs Historical Optimization
long-only strategy
27 U.S. REITs

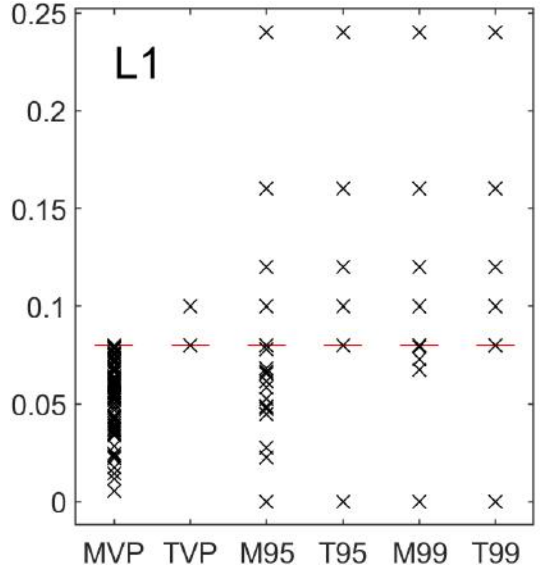
Dynamic



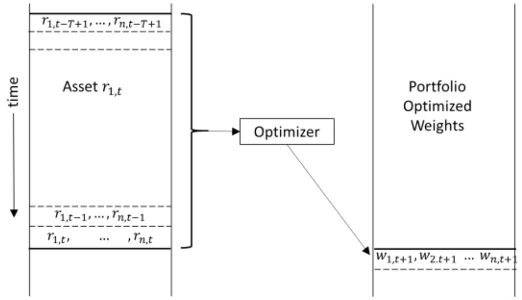
Cumulative price

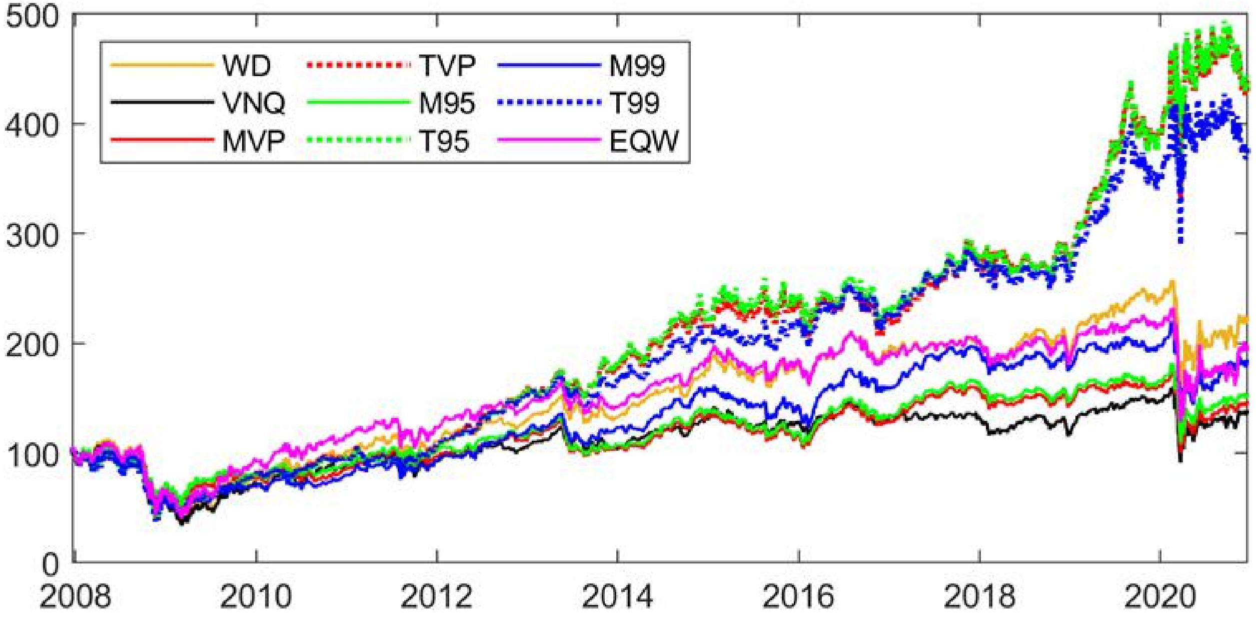


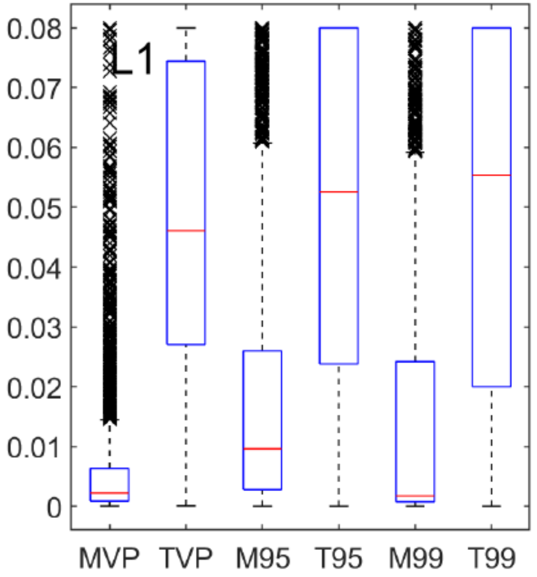
Turnover statistics



Historical





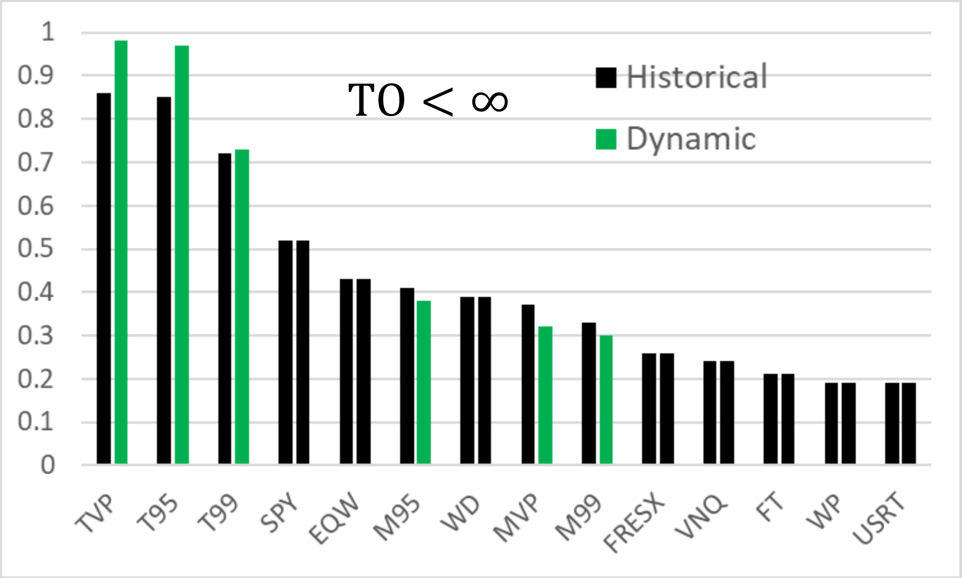


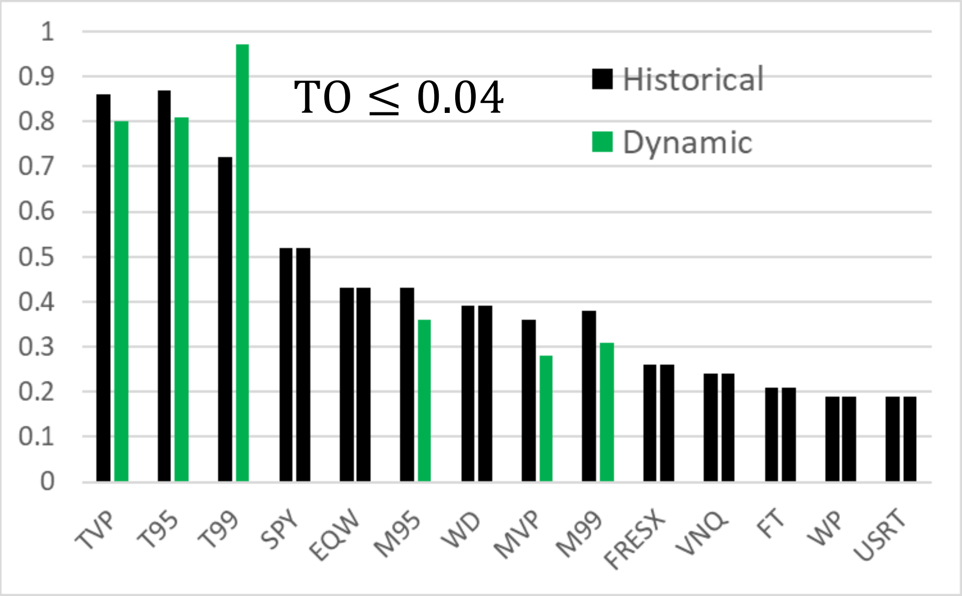
Performance measures

12/17/2008 – 12/18/2020 average score combined

total return, maximum drawdown, Sharpe ratio, Sortino-Satchell ratio, Rachev ratio

Optimized portfolios compared to benchmarks





Trend-Persistent* (Momentum) Strategies for Intraday Trading (27 U.S. REITs)

α[1]	L ($)[2]	Total return (%) period[3]	Total return (%) ann'd	CVaR[4]	CVoR[5]	MDD[6]
Long-short based on Sharpe ratio, $t_{\text{form}} = 5$, no optimization						
n.a.	100	17.6	66.6	-0.209	0.225	0.214
Zero investment long-short, cash cushioned						
0.00	200	44.6	220	-0.210	0.223	0.076
0.25	500	129.6	1,277	-0.438	0.466	0.207
0.75	100	20.2	78.8	-0.129	0.133	0.071
0.95	100	22.0	87.3	-0.119	0.126	0.048
Buy and hold (no optimization, no adjustment)						
n.a.	n.a.	19.7	76.5	-0.136	0.1219	0.071
Winner-loser adjusted, long						
0.75	100	23.0	92.2	-0.110	0.110	0.085
0.95	100	23.0	92.3	-0.110	0.110	0.085
Composite: buy & hold + long/short						
0.00	200	24.3	98.3	-0.126	0.120	0.066
0.00	500	27.2	113	-0.125	0.121	0.057
0.25	200	22.2	88.2	-0.129	0.122	0.067
0.25	500	32.8	144	-0.123	0.120	0.055
0.75	1000	35.7	162	-0.140	0.140	0.058
0.95	1000	35.7	161	-0.140	0.141	0.060

* $t_{\text{formation}} = 200$ min
$t_{\text{hold}} = 30$ min

[1] $\max\left(\alpha E(r_{p,t+1}) - (1-\alpha)\,\text{CVaR}_{95,t+1}\right)$
$\alpha = 0$: minimum risk portfolio
$\alpha = 1$: maximum return portfolio

[2] Short 3 expected losers @ $-\$L/3$
Long on 3 expected winners @ $+\$L/3$

[3] 1/12/2021 to 5/05/2021
[4] conditional value-at-risk (95% CL)
[5] conditional value-of-return (95% CL)
[6] maximum drawdown over period

buy & hold initial investment $10,000

Performance ratios

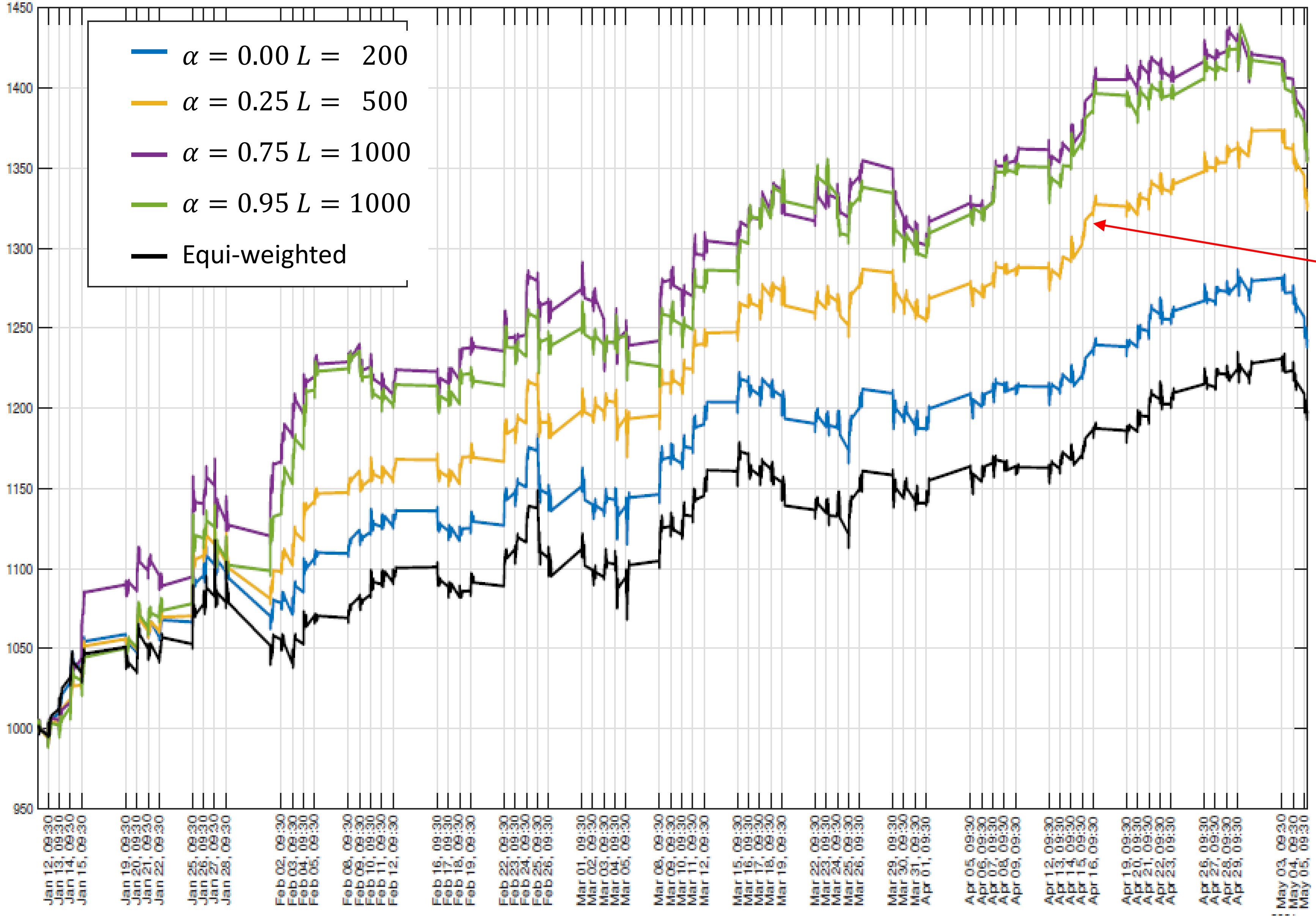
α[1]	L ($)[2]	Sharpe	Sortino	STAR	Rachev	Gini
Long-short based on Sharpe ratio, $t_{\text{form}} = 5$, no optimization						
n.a.	100	0.51	0.80	0.25	107.4	1.25
Zero investment long-short, cash cushioned						
0.00	200	1.20	1.86	0.58	106.2	2.76
0.25	500	1.26	2.01	0.62	106.5	3.14
0.75	100	0.96	1.46	0.47	103.2	2.26
0.95	100	1.11	1.74	0.55	105.5	2.60
Buy and hold (no optimization, no adjustment)						
n.a.	n.a.	1.00	1.36	0.44	94.6	2.15
Winner-loser adjusted, long						
0.75	100	1.34	1.89	0.62	99.9	2.91
0.95	100	1.27	1.80	0.58	99.3	2.80
Composite: buy & hold + long/short						
0.00	200	1.29	1.77	0.57	95.2	2.81
0.00	500	1.44	2.02	0.63	96.4	3.14
0.25	200	1.18	1.61	0.51	94.5	2.54
0.25	500	1.72	2.42	0.76	97.6	3.78
0.75	1000	1.57	2.27	0.72	100.1	3.53
0.95	1000	1.58	2.32	0.72	100.3	3.51

$$\text{Sharpe} = \frac{E[r_p - r_f]}{\sigma_{r_p - r_f}} \qquad \text{Sortino} = \frac{E[r_p - r_f]}{\left(\sigma_{r_p - r_f}\right)^-}$$

$$\text{STAR} = \frac{E[r_p - r_f]}{\text{CVaR}_{95}[r_p - r_f]} \qquad \text{Rachev} = \frac{\text{CVoR}_{95}[r_p - r_f]}{\text{CVaR}_{95}[r_p - r_f]}$$

$$\text{Gini} = \frac{E[r_p - r_f]}{-\gamma \operatorname{cov}\left\{\left(r_p, \left[1 - F\left(r_p\right)\right]^{\gamma - 1}\right\}}, \gamma = 1.1$$

Horse-race comparison: Composite: buy and hold + long/short



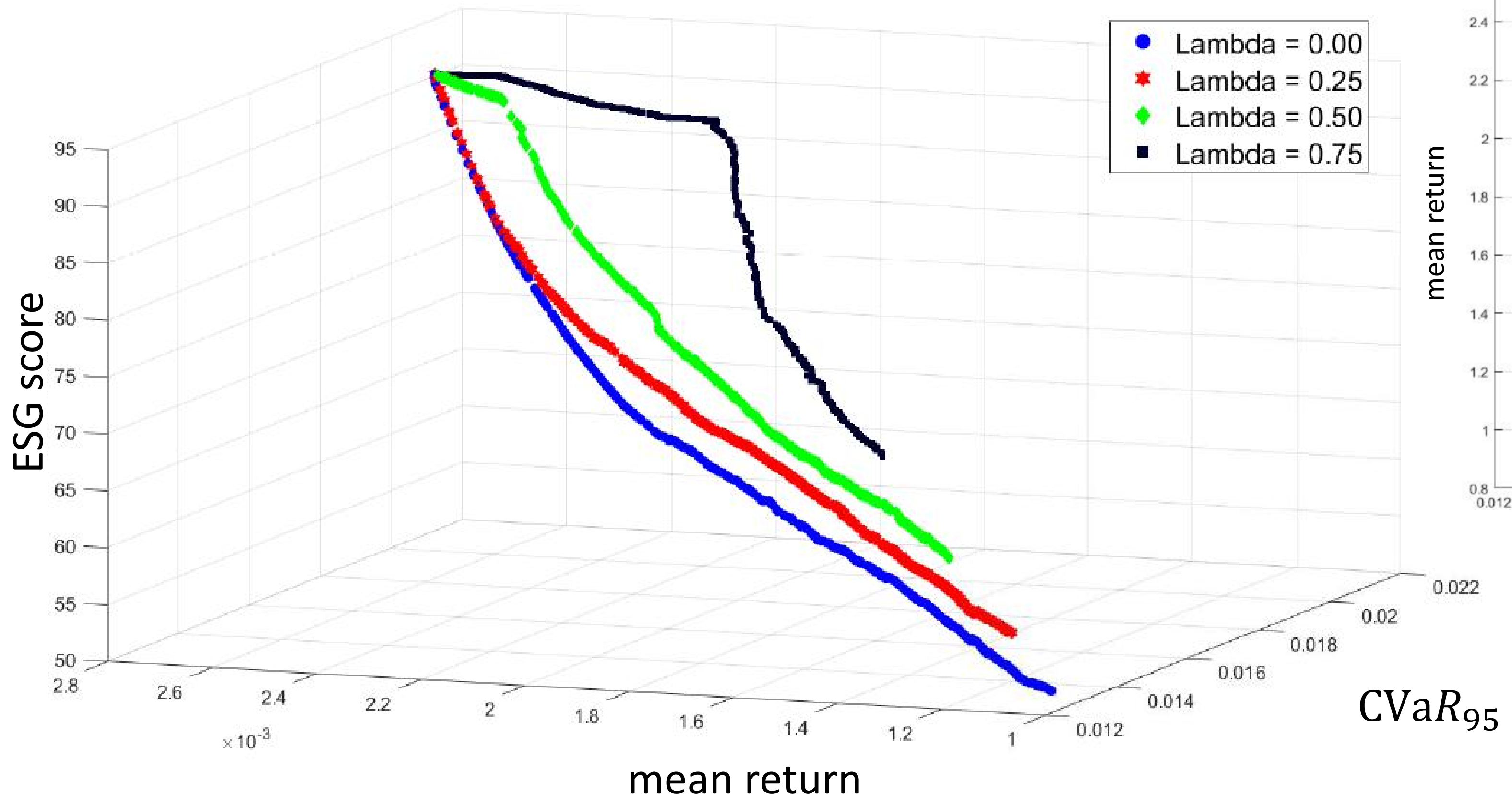
Jantz recommendation

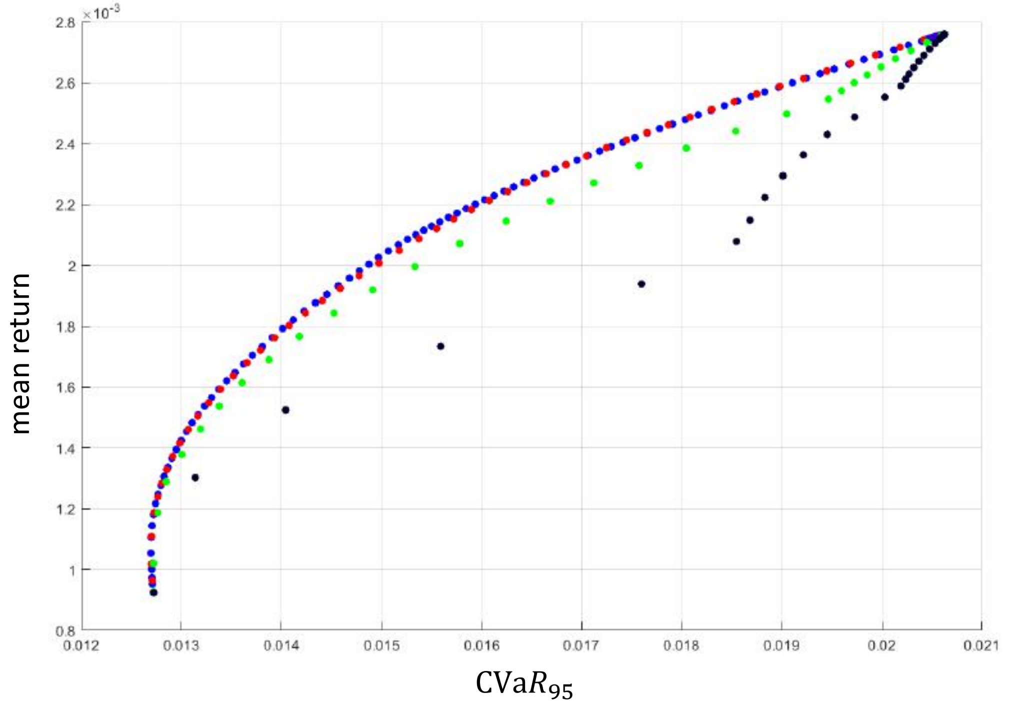
ESG Score in Portfolio Optimization (DOW 30)

$V(r_{p,t})$: portfolio risk measure e.g. $\mathrm{CVa}R_{95}$
$E(r_{p,t})$: expected portfolio return
$\Gamma_{i,t}$: standardized ESG score for asset i
$r_{i,t}$: return for asset i

$$\text{Maximize}\left\{\alpha\, E\left(r_{p,t+1}^{(\mathrm{ESG})}\right) - (1-\alpha)\,\mathrm{CVaR}_{95}\left(r_{p,t+1}^{(\mathrm{ESG})}\right)\right\}$$

$$\text{where } r_{p,t+1}^{(\mathrm{ESG})} = \sum_{i=1}^{n} w_i\left[\lambda\,\mathrm{ESG}_{i,t+1} + (1-\lambda)\, r_{i,t+1}\right]$$





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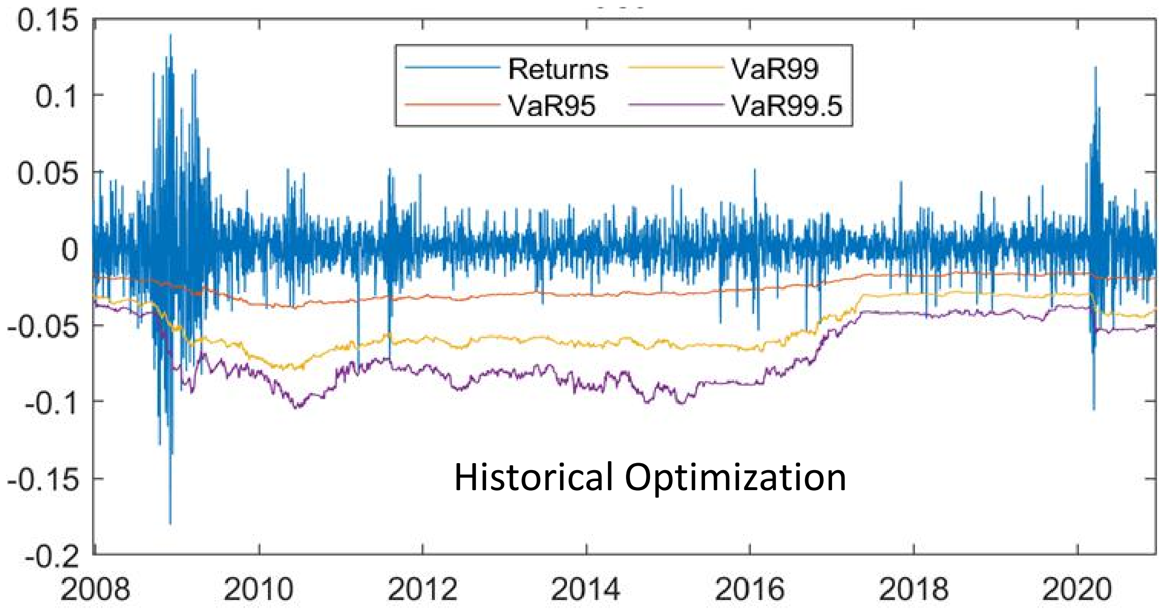
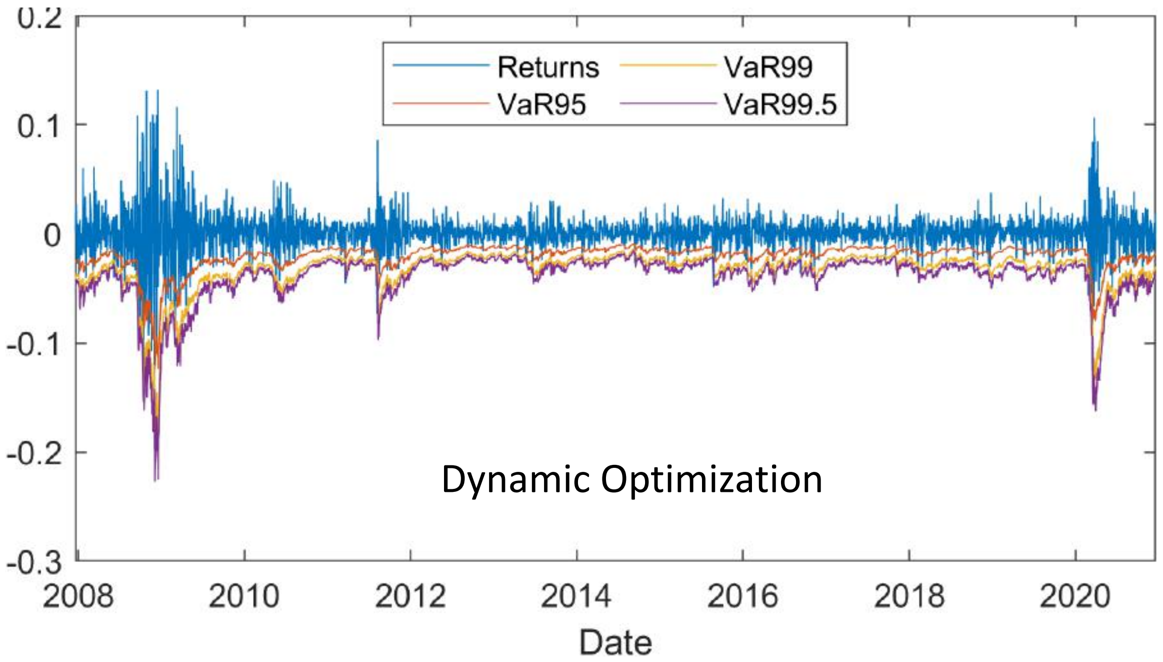
Backtesting (TVP, 27 U.S. REITs)





$1-\alpha$	TL	BIN p_{BIN}	PoF p_{POF}	TUFF p_{TUFF}	CCI p_{CCI}	TBFI p_{TBFI}	CC p_{CC}	TBF p_{TBF}
0.95	0.9827	0.035	0.039	0.237	$1.8 \cdot 10^{-8}$	$< 10^{-40}$	$1.5 \cdot 10^{-8}$	$< 10^{-40}$
0.99	1.0000	$6.8 \cdot 10^{-7}$	$9.2 \cdot 10^{-6}$	0.089	$9.2 \cdot 10^{-8}$	$< 10^{-30}$	$3.4 \cdot 10^{-11}$	$< 10^{-33}$
0.995	1.0000	$1.2 \cdot 10^{-5}$	$1.4 \cdot 10^{-4}$	0.041	$1.6 \cdot 10^{-5}$	$< 10^{-25}$	$6.5 \cdot 10^{-8}$	$< 10^{-27}$

	$1-\alpha$	TL $P(X \leq x \mid N, \alpha)$	BIN p_{BIN}	PoF p_{POF}	TUFF p_{TUFF}	CCI p_{CCI}	TBFI p_{TBFI}	CC p_{CC}	TBF p_{TBF}
Basel I	0.95	0.979	0.042	0.047	0.237	0.035	6.810^{-7}	0.015	4.010^{-7}
	0.99	0.952	0.103	0.119	0.089	0.017	0.004	0.017	0.003
Basel II	0.995	0.955	0.100	0.121	0.616	0.568	0.123	0.256	0.096

TL – Basel II traffic light test

BIN – binomial test

PoF – proportion of failures (Kupiec, 1995)

TUFF – time until first failure (Kupiec, 1995)

CCI – conditional coverage independence (Christoffersen, 1998)

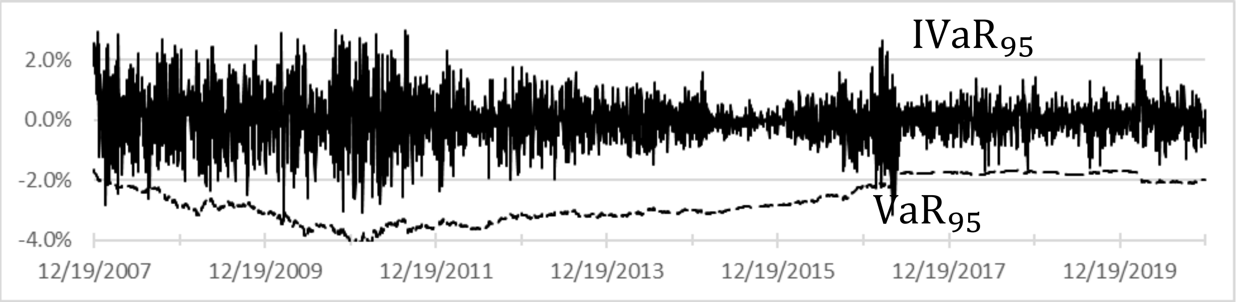
CC – conditional coverage (PoF + CCI)

TBFI – time between failures independence test (Haas, 2001)

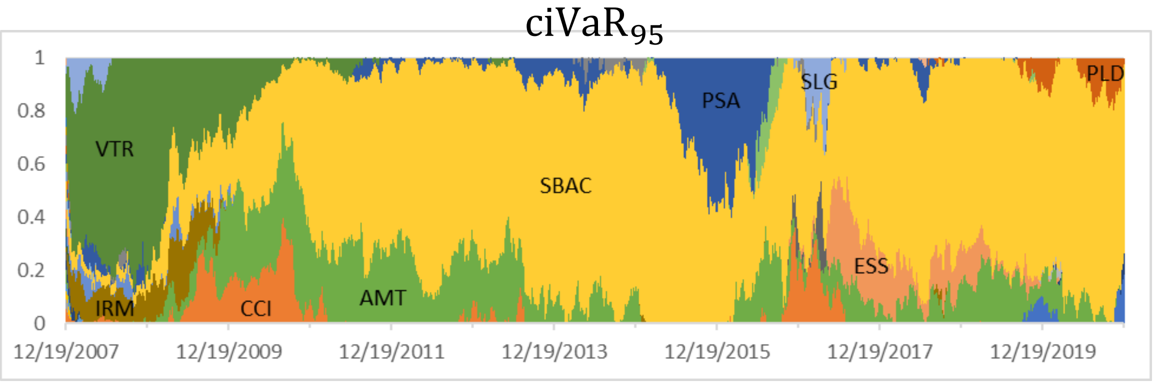
TBF – time between failures (PoF + TBFI)

Risk Analytics

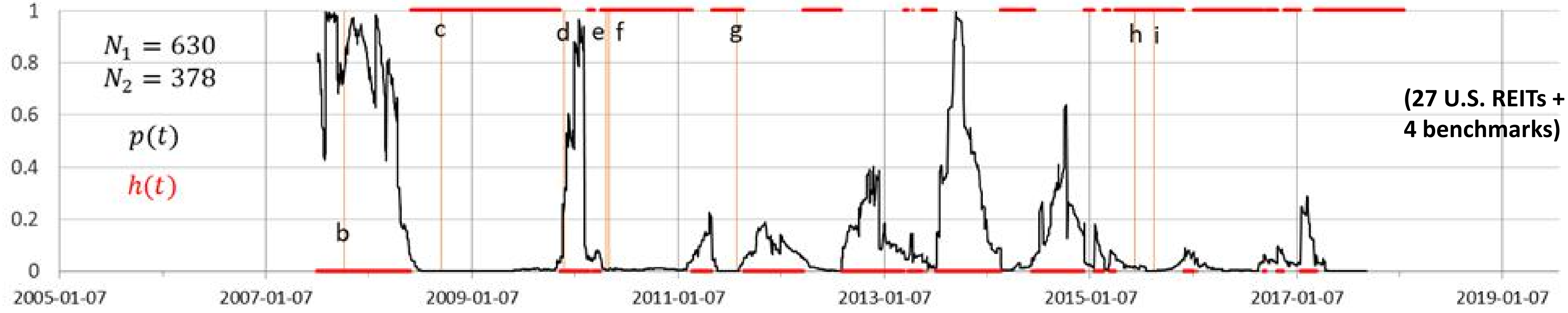
Monitor daily total (VaR), incremental (IVaR), and component ciVaR value-at-risk



(TVP, 27 U.S. REITs)



Early Warning: Search for precursor signals in the correlation structure of assets prior to a shock



(27 U.S. REITs + 4 benchmarks)

Structural breaks detected commensurate with almost every one of the major world market upheavals over this time-period

b: US bear market; c: great recession; d: Dubai debt standstill; e: European sovereign debt crisis;
f: US flash crash; g: US Aug 2011 decline; h: China crash; i: US market selloff

Improved Asset Pricing
Intrinsic-Time Volatility

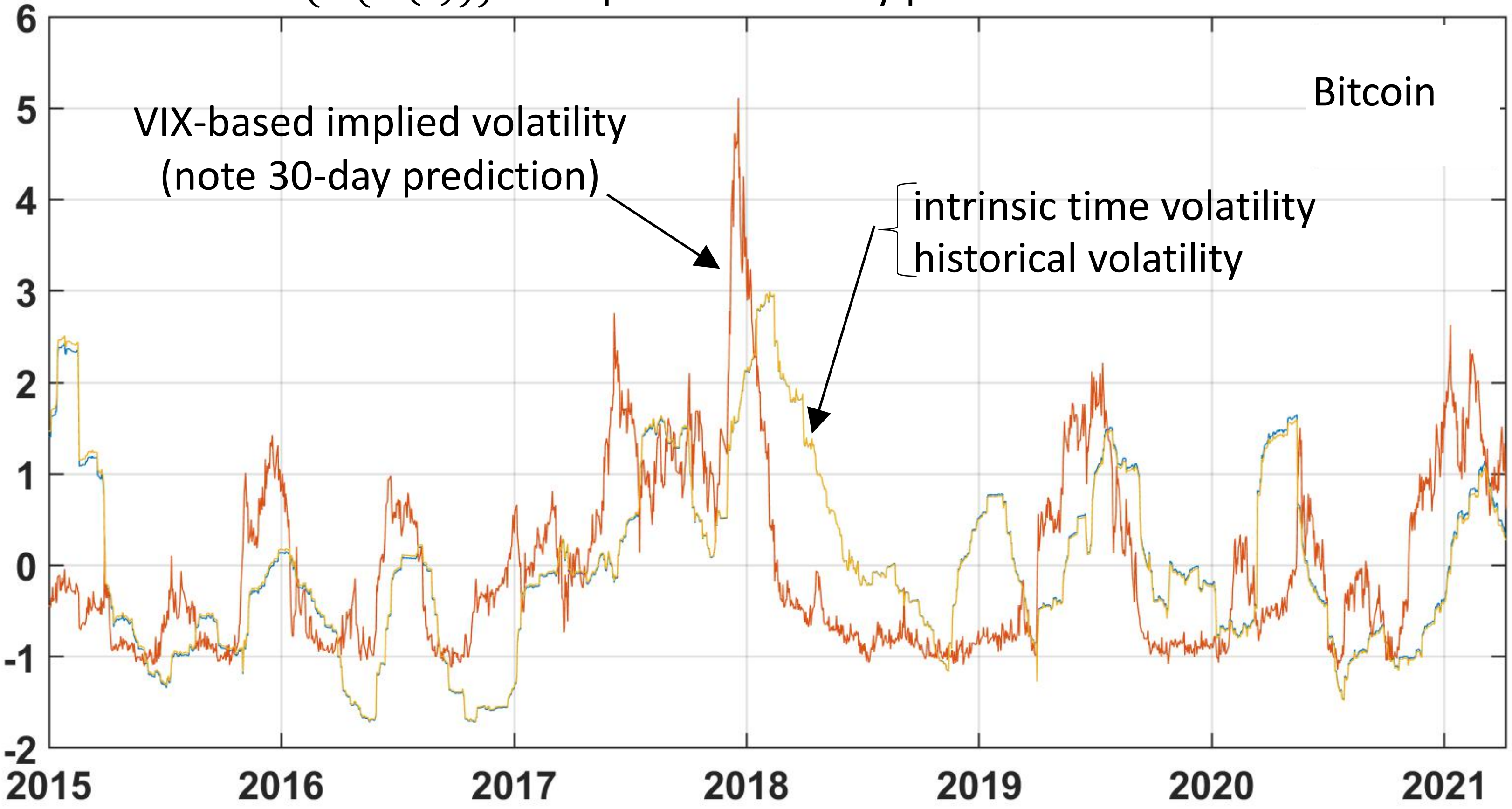
Brownian motion (produces Gaussian, symmetric returns)

Classic model: $S_t = S_0 e^{X_t}, \ \ X_t = \mu t + \sigma B_t$

Double subordination: $X_t = \mu t + \sigma B_{\mathcal{T}(U(t))}$

subordinated Lévy processes $\mathcal{T}(U(t))$
$\mathcal{T}$ transforms Gaussian returns in unit time
→ skewed and heavy-tailed returns in unit time
U transforms SH-T return events from unit-time spacing
→ random time (intrinsic time) spacing

$\sigma^2 \rightarrow \sigma^2 \, \mathrm{Var}(\mathcal{T}(U(t)))$ → improved volatility prediction



To do

- Test momentum intraday strategies on crypto assets and Russell 3000
- Reformulate optimal momentum intraday strategy as a mixed integer programming problem for Dow 30, REITs, cryptos, and Russell 3000
- Implement dynamic factor models for monthly returns for Dow 30, REITs, cryptos, and Russell 3000
- Complete option pricing based on REIT daily returns
- Complete ESG optimization and ESG option pricing for daily returns for Dow 30, REITs, cryptos, and Russell 3000

Thank You

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