Do Public Equities Span Private Equity Returns?

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Motivation

"Alternative assets, including private equity , offer the possibility of superior returns and diversification benefits not available in traditional asset classes such as publicly traded stocks and bonds."

—**David Swensen**, the legendary CIO of Yale's Endowment
"Pioneering Portfolio Management" (2000)

Our question:

How much PE can truly move the efficient frontier

(beyond the delusions that appraisal-based valuations may induce)

What do we do?

1. Using recent advances in filtering PE returns at high frequency and in return factors identification, we:

- test whether a rich panel of PE returns contains factors that are absent from a mimicking public equity panel
- study characteristics of PE-specific factors and their impact on portfolios
- conduct inference about optimal PE allocation

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2. **We find that PE-specific factors:**
   - are present in the data and drive about 3.3 pp of annualized returns
   - significantly improve the maximal Sharpe ratio and reduce GMV risk
     - yet, PE shorting constraint eliminates much of the gains (but not all!)
   - justify an allocation of 11-24% by liquidity unconstrained investors
   - are mostly distinct across PE data providers
     - even though the common factors with public equities are very close

Contribution

1. Performance and portfolio choice with PE: Kaplan & Schoar (2005), Harris, Jenkinson & Kaplan (2014), Robinson & Sensoy (2016), Korteweg & Nagel (2016), Ang, Chen, Goetzmann & Phalippou (2018), Gredil, Sorensen & Waller (2020), Gupta & Van Nieuwerburgh (2021), Giommetti & Sorensen (2021), Korteweg & Nagel (2024), Gourier, Phalippou & Westerfield (2024)

- **do not (explicitly) take an stand on** what the **SDF** is
- static portfolios of public equities (industries, anomalies, ...) cannot explain our results
- examine the effect of active sector weights within PE

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    - that price the cash flows perfectly for each portfolio
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3. Cross-section shrinkage to salient factors: Chamberlain & Rothschild (1983), Fama & French (1993, 2015), Hou, Xue & Zhang (2015), Kozak, Nagel & Santosh (2018, 2020), Feng, Giglio & Xiu (2020)

- new asset class examined, comparison of different sources of conceptually same data

Data sources

Private equity

- MSCI PC Universe (fmr. Burgiss): almost 5k of various PE-like funds
  - vintaged between 1995 and 2018, focused on North America
  - Distr.debt–Infra–RE–NatRes–Buyout—Venture(by-stage)
  - cross-checked and dated: cash calls&distributions, quarterly NAV reports
  - portfolio-level weights breakdown by industry

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- which *weekly return nowcasts* are grouped into 50 indices (PERs)
  - {Fund styles}×{Size cuts}×{Industries}: 2003w1–2013w52
  - price each index's cash flows to have NPV of 0
  - exhibit every trait of a liquid asset return
- In additional and robustness tests:
  - MSCI PC without fund investment geo restrictions
  - Preqin fund cash flow database augmented with deal-level data from StepStone

Public equity

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Public equity

- the Comparable Assets (CARs)
  - Style-by-Size-by-Industry matched to fund investment weights
  - each fund-week return value-weighted to the indices level
- Fama-French 5 factors
- U.S. equity factor Zoo (Chen and Zimmermann, 2022)
  - 199 (out of 213) “species” that lived over 2003w1–2023w52
  - the ‘long beta’ factor swapped out with the FF market factor

What is *nowcasting* PE returns?

Intuition

The idea in Brown, Ghysels, Gredil (2023) is to treat PE fund data, as well related data such as comparable asset performance, as imperfect signals:

$$
\begin{aligned}
\mathrm{fundDistribution}_t &= f(\mathrm{bias1}_t, \mathrm{noise1}_t, \ldots) \cdot \boldsymbol{R_t} && \text{irregular} \\
\mathrm{fundNetAssetValue}_{t-1} &= g(\mathrm{bias2}_{t-1}, \mathrm{noise2}_{t-1}, \ldots) \cdot \boldsymbol{R_{t-1}} && \text{last week of quarter} \\
\mathrm{ComparableAsset}_{t+1} &= h(\mathrm{bias3}_{t+1}, \mathrm{noise3}_{t+1}, \ldots) \cdot \boldsymbol{R_{t+1}} && \text{every week}
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Because the economic nature of the biases&noise is different across the observed data types, we can model/filter them out via SSMs to estimate "true return" process, $\boldsymbol{R_t}$

- Code available at `https://github.com/orgredil/Nowcasting-PE-NAVs/tree/main`.

What is *nowcasting* PE returns?

Model

Latent at weekly frequency

$\boldsymbol{R_t}$:	Gross return of the fund $\equiv \exp\{\boldsymbol{r_t}\}$	$r_{0:t}$:	Log returns from inception until $t := \sum_{\tau=0}^{t} r_\tau$
$\bar{r}_{0:t}$:	Smoothed log returns from inception until t	V_t:	True asset value of the fund $:= \exp\{r_{0:t} - m_t\}$

Observed at weekly frequency

R_{mt}:	Gross return on the market	h_t:	The common factor of conditional variance in idiosyncratic returns of $\boldsymbol{R_t}$ and R_{ct}
R_{ct}:	Gross return on Comparable Asset		
V_t^0:	Naïve nowcasts of fund NAVs	w_t:	Fraction of $C_t + D_t$ in $V_t^0 + D_t$

Observed at low (e.g. quarterly) or irregular frequency

NAV_t:	NAVs of the fund, as reported by the fund's manager	D_t:	Distributions from the fund
		C_t:	Capital calls by the fund

$$R_t = \exp\{\alpha + \beta r_{mt} + \eta_t\}$$

$$R_{ct} = \exp\{\psi + b \cdot r_{mt} + \beta_c \cdot \eta_t + \eta_{ct}\}$$

$$\bar{r}_{0:t} = \left(1 - \lambda(\cdot)_t\right) r_{0:t} + \lambda(\cdot)_t \bar{r}_{0:t-1}$$

$$R_{ct} = \exp\{a + b \cdot r_{mt} + e_t\}$$

$$\log(D_t) = \overbrace{r_{0:t} - \hat{m}_t}^{\text{log of true asset value}} + \text{logit}(\delta(\cdot)_t) + \epsilon_{d,t}$$

$$\log(\text{NAV}_t) = \underbrace{\bar{r}_{0:t} - \hat{m}_t}_{\text{log of smoothed asset value}} + \epsilon_{n,t}$$

$$\delta(\cdot)_t = \min(0.99,\ \delta \cdot t/52)$$

$$\lambda(\cdot)_t = \lambda \cdot (1 - w_t)$$

with $e_t \sim \mathcal{N}(0, h_t)$, $\eta_t \sim \mathcal{N}(0, F^2 \cdot h_t)$, $\eta_{ct} \sim \mathcal{N}(0, {F_c}^2 \cdot h_t)$, $\epsilon_{nt} \sim \mathcal{N}(0, {\sigma_n}^2)$, $\epsilon_{dt} \sim \mathcal{N}(0, {\sigma_d}^2)$

What is *nowcasting* PE returns?

Model

Fund's risk-return

β:	systematic risk	F:	h_t-normalized idiosyncratic risk
α:	abnormal return		

Fund's reporting quality | *Fund's distribution process*

λ:	smoothing intensity, $\lambda(\cdot)_t$ is scalar fn	δ:	distribution's intensity trend, $\delta(\cdot)_t$ is scalar fn
σ_n:	reporting noise	σ_d:	distribution's intensity noise

Comparable Asset

β_c:	slope to the fund's idiosync. return	F_c:	h_t-normalized idiosyncratic risk level to the fund's returns
ψ:	log return intercept to the fund		

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For an intuitive Kalman Filter representation, assume:
($\lambda = 0$, weekly NAV reports, no interim cash flows) $\Rightarrow$ $\Delta.\log(NAV_t) = r_t + \Delta.\epsilon_{nt} \equiv \Delta.v_t$

$$r_t = K_v\,\Delta.v_t + \alpha(1-K_v) + \beta(1-K_v)\,r_{mt} + K_c\,\boldsymbol{e_t} \quad ,$$

$$\text{where} \quad K_v = \frac{{F_c}^2 h_t}{{F_c}^2 h_t + 2{\beta_c}^2{\sigma_n}^2} \quad , \quad K_c = \frac{2\beta_c\,{\sigma_n}^2}{{F_c}^2 h_t + 2{\beta_c}^2{\sigma_n}^2} \quad , \qquad K_c\beta_c + K_v = 1$$

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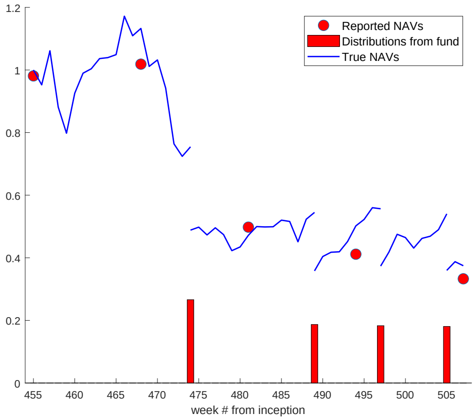
What is *nowcasting* PE returns?

Estimation details

Simulated example

"True" NAVs are blue line, reported NAVs (red dots) in weeks 455, 468, 481, 494, and 507, cash distributions (red bars) in weeks 474, 489, 497, and 505, asset value nowcasts are dotted lines. Nowcast errors are -1 plus the ratio of the nowcasts to true NAVs. The fund fully resolves on week 562.

True returns vs Obs. data



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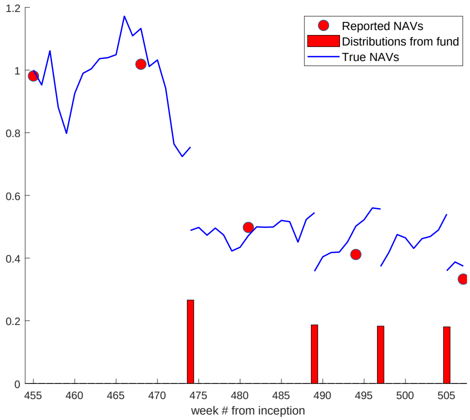
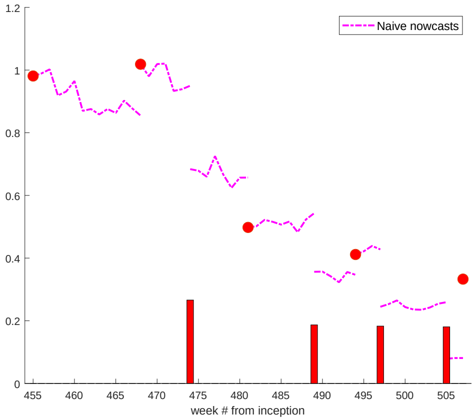


A Simple method to nowcast



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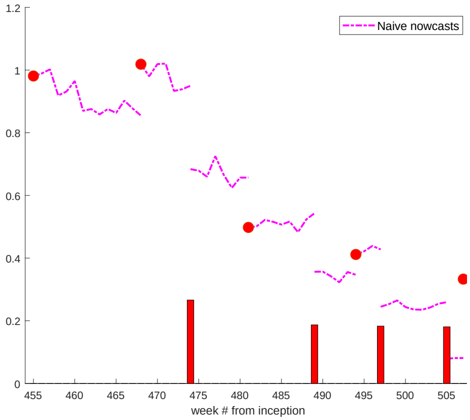
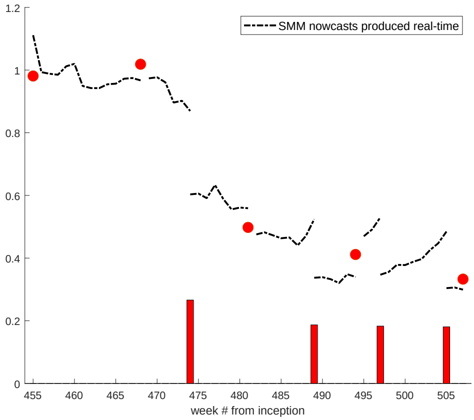


BGG method (in real-time)



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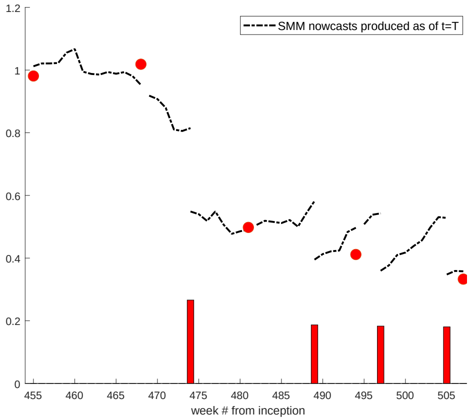

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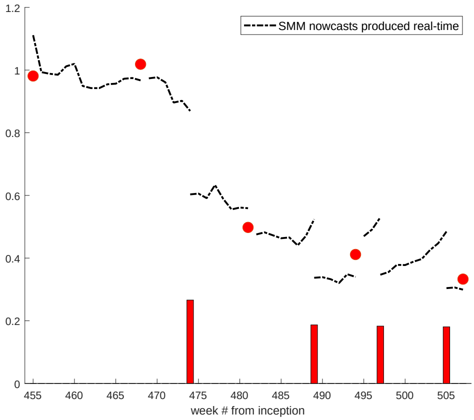

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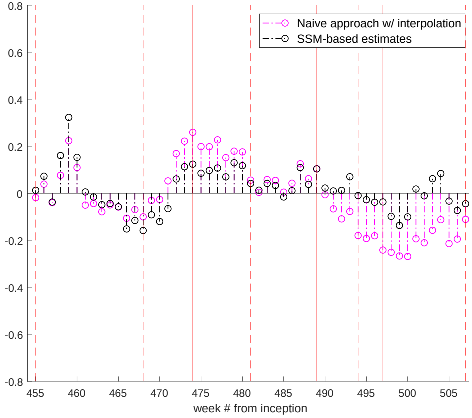
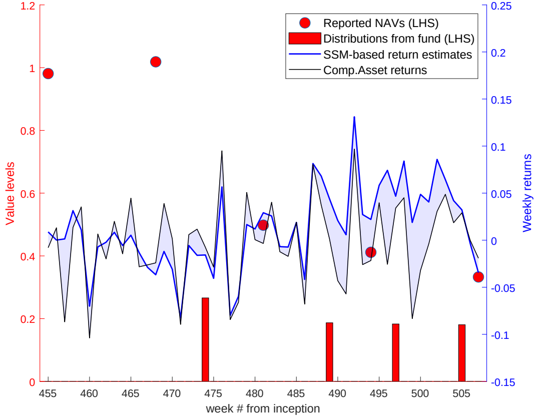
Asset value estimation errors (t=562)



When do CA and SSM estimates diverge?



Fund-level SSMs for our sample

	(N = 4,892)					
	mean	sd	p10	p25	p75	p90
Fund size (bln)	0.710	(1.38)	0.068	0.150	0.688	1.494
Fund vintage	2007	(7.66)	1997	2000	2014	2017
α: Abnormal return (annualized)	0.026	(0.16)	-0.135	-0.054	0.102	0.183
β: Market risk	1.119	(0.34)	0.659	0.865	1.382	1.548
β_c: CA loading on Fund idret	0.212	(0.25)	0.010	0.020	0.260	0.695
F: Fund-to-CA id.volty. ratio	3.112	(2.11)	1.082	1.875	3.504	4.700
λ: NAV smoothing	0.888	(0.16)	0.725	0.865	0.972	0.987
σ_n: NAV noise	0.063	(0.03)	0.025	0.040	0.080	0.106
δ: Distribution size mean	0.021	(0.04)	0.005	0.009	0.022	0.036
σ_d: Distributions size volty	1.279	(0.68)	0.578	0.850	1.616	2.121
In-sample RMSE	0.057	(0.34)	0.003	0.008	0.053	0.113
RMSE improvement (%)	61.73	(36.5)	20.24	53.27	84.28	91.34
AR(1) on nowcasted returns	0.012	(0.13)	-0.109	-0.075	0.057	0.165

Comparable asset construction and aggregation to index-level

Fund-Level Comparable Asset, R_{ct}

- For each fund it is comprised of:
  1. **Spanned weight**:
     $\sum$ of top 3 industries by invested amount, matched to resp. industry benchmarks:
     - Fama-French 12 industries
     - RE and Energy splits by size
  2. **Unspanned weight**:
     $= 1 - \sum(\text{Top3 Ind})$ matched to:
     - closest Fama-French 25 benchmark
     - excl. 10 largest & extreme growth/value
- Fixed weights throughout fund's life

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Example: For a large Buyout fund with 30% invested in Consumer Durables, 20% in Healthcare, 10% in Industrials, $R_{ct} - 1 = [\text{durbl}_t \quad \text{hlth}_t \quad \text{manuf}_t \quad \text{BM4ME3}_t] \cdot [0.30 \quad 0.20 \quad 0.10 \quad 0.40]'$

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Index-Level Aggregation

- **PE Index Returns (SSM VW nowcasts)**:
  - Value-weighted returns using weights proportional to SSM-based NAV estimates from previous week (V_{t-1})
  - Applied to individual fund PE return estimates R_t
- **Comparable Asset Returns (CARs)**:
  - Value-weighted returns using weights proportional to naïve NAV nowcasts from previous week
  - Applied to fund-level comparable asset returns R_{ct}

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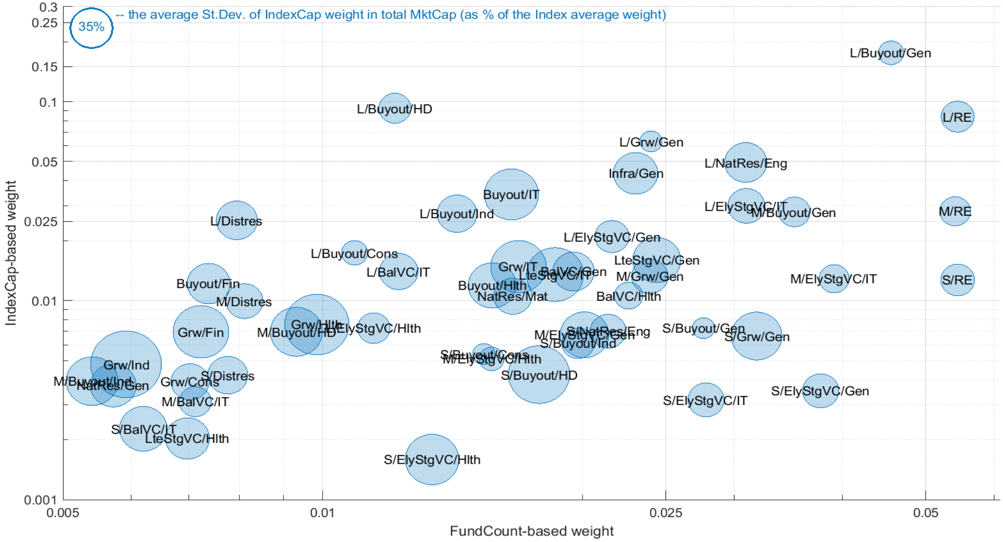
PE portfolios for spanning tests

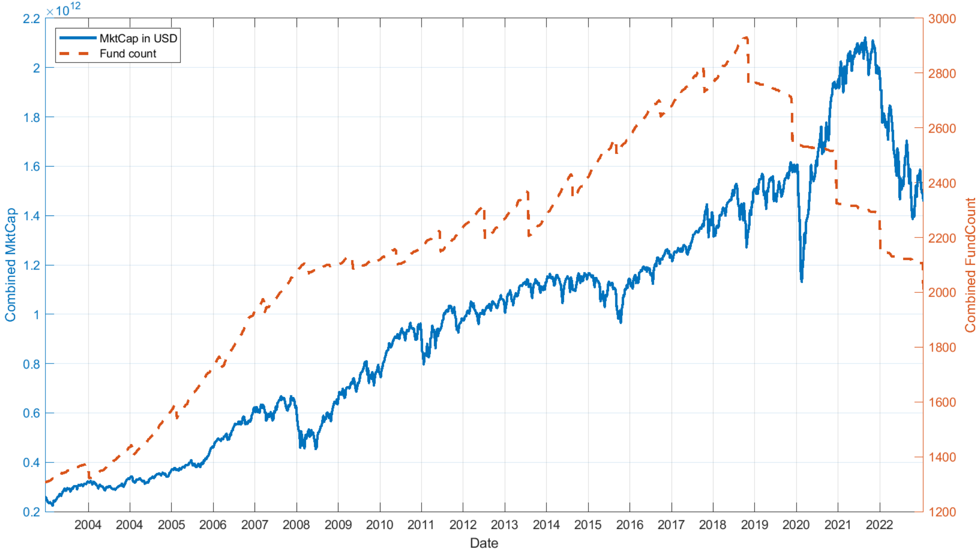
3 col. of { Index Name Sample-average fund population Sample-average capitalization ($b) }

L/Distres	9.6	23.66	M/Distres	11.4	9.21	S/Distres	11.6	3.57
L/NatRes/Eng	10.3	53.77				S/NatRes/Eng	13.5	6.45
NatRes/Gen	9.9	3.33	NatRes/Mat	9.9	10.53	Infra/Gen	11.7	49.35
L/RE	34.9	83.08	M/RE	39.0	25.43	S/RE	41.3	11.26
L/Buyout/HD	15.6	91.09	M/Buyout/HD	25.4	5.23	S/Buyout/HD	43.5	2.89
L/Buyout/Gen	39.9	165.29	M/Buyout/Gen	30.4	24.99	S/Buyout/Gen	16.3	7.03
L/Buyout/Cons	13.2	17.48				S/Buyout/Cons	12.9	5.30
L/Buyout/Ind	14.8	23.73	M/Buyout/Ind	9.8	3.37	S/Buyout/Ind	16.1	6.43
Buyout/Fin	11.3	11.13	Buyout/Hlth	10.6	12.24	Buyout/IT	12.1	42.21
L/Grw/Gen	22.2	60.94	M/Grw/Gen	29.3	12.28	S/Grw/Gen	42.8	5.18
Grw/Cons	10.7	3.57	Grw/Fin	11.1	5.54	Grw/Hlth	12.3	6.30
Grw/Ind	12.3	2.98	Grw/IT	14.3	18.14			
L/ElyStgVC/Gen	26.3	22.77	M/ElyStgVC/Gen	27.4	8.00	S/ElyStgVC/Gen	54.1	3.67
L/ElyStgVC/Hlth	9.1	7.80	M/ElyStgVC/Hlth	11.3	4.85	S/ElyStgVC/Hlth	17.6	1.15
L/ElyStgVC/IT	48.9	26.71	M/ElyStgVC/IT	50.5	11.82	S/ElyStgVC/IT	21.7	3.36
L/BalVC/IT	17.1	12.56	M/BalVC/IT	12.4	2.97	S/BalVC/IT	11.5	1.95
BalVC/Gen	43.8	15.93	BalVC/Hlth	16.9	9.93			
LteStgVC/Gen	21.4	19.25	LteStgVC/Hlth	12.2	1.80	LteStgVC/IT	15.3	16.68

PE portfolios for spanning tests



Trends in combined valuation and fund counts



The time series of the sum of fund counts and asset value estimates across PE indices used in the analyses.

PE index portfolios' diagnostics

Select characteristics	(N = 50, T = 1,040)					
	mean	sd	p10	p25	p75	p90
Averages by index:						
Fund age	5.37	(0.64)	4.53	4.95	5.82	6.31
Fund size ($b)	0.72	(0.93)	0.16	0.22	0.69	1.40
Fund count	43.3	(27.3)	15.1	20.2	52.8	83.2
Index Cap ($b)	19.7	(29.2)	2.97	4.85	22.8	51.6
Totals by index:						
# weeks with Calls	785	(154)	566	653	902	986
# weeks with Dist.	786	(189)	573	649	909	1052

The **indices are value-weighted—**
by the previous week's asset value nowcast of the constituent funds

For the vast majority of indices, distributions are observed in more than half of the weeks (in addition to 80 weeks with NAV reports)—**hope to identify PE factors!**

PE index portfolios' diagnostics

PMEs against select benchmarks	(N = 50)					
	mean	p10	p25	p50	p75	p90
SSM-based last NAVs:						
vs. Broad market	1.29	1.01	1.13	1.28	1.43	1.57
vs. Comp assets (CARs)	1.11	0.75	1.02	1.15	1.25	1.33
vs. SSM VW nowcasts	1.01	0.97	0.99	1.00	1.02	1.04
vs. SSM EW nowcasts	1.23	1.04	1.11	1.20	1.32	1.42
As reported last NAVs:						
vs. Broad market	1.30	1.01	1.13	1.28	1.45	1.59
vs. Comp assets (CARs)	1.11	0.75	1.01	1.15	1.25	1.37
vs. SSM VW nowcasts	1.01	0.97	0.99	1.01	1.02	1.05
vs. SSM EW nowcasts	1.23	1.03	1.10	1.19	1.31	1.45

Size-x-style-x-industry rotation explains **two-thirds of Private Equity outperformance** to the broad public market index

PE index portfolios' diagnostics

PMEs against select benchmarks	(N = 50)					
	mean	p10	p25	p50	p75	p90
SSM-based last NAVs:						
vs. Broad market	1.29	1.01	1.13	1.28	1.43	1.57
vs. Comp assets (CARs)	1.11	0.75	1.02	1.15	1.25	1.33
vs. SSM VW nowcasts	1.01	0.97	0.99	1.00	1.02	1.04
vs. SSM EW nowcasts	1.23	1.04	1.11	1.20	1.32	1.42
As reported last NAVs:						
vs. Broad market	1.30	1.01	1.13	1.28	1.45	1.59
vs. Comp assets (CARs)	1.11	0.75	1.01	1.15	1.25	1.37
vs. SSM VW nowcasts	1.01	0.97	0.99	1.01	1.02	1.05
vs. SSM EW nowcasts	1.23	1.03	1.10	1.19	1.31	1.45

Despite a 99% correlation with EW index returns, only VW index returns price VW cash flows across indices

PE index portfolios' diagnostics

PMEs against select benchmarks	(N = 50)					
	mean	p10	p25	p50	p75	p90
SSM-based last NAVs:						
vs. Broad market	1.29	1.01	1.13	1.28	1.43	1.57
vs. Comp assets (CARs)	1.11	0.75	1.02	1.15	1.25	1.33
vs. **PERs**	1.00	1.00	1.00	1.00	1.00	1.00
vs. SSM EW nowcasts	1.23	1.04	1.11	1.20	1.32	1.42
As reported last NAVs:						
vs. Broad market	1.30	1.01	1.13	1.28	1.45	1.59
vs. Comp assets (CARs)	1.11	0.75	1.01	1.15	1.25	1.37
vs. SSM VW nowcasts	1.01	0.97	0.99	1.01	1.02	1.05
vs. SSM EW nowcasts	1.23	1.03	1.10	1.19	1.31	1.45

For the main analyses, an index-specific constant is added to VW returns to ensure cash flow NPVs are exactly zero for each index: $\text{PERs}_{it} = \text{SSM VW nowcasts}_{it} + a_i$

Framework

Two panels of returns as per the **group-factor model** of Gagliardini et al. (2019):

$$\left[\begin{array}{c} y_{Pr,\tau} \\ y_{Pu,\tau} \end{array}\right] = \left[\begin{array}{ccc} \Lambda^c_{Pr} & \Lambda^s_{Pr} & 0 \\ \Lambda^c_{Pu} & 0 & \Lambda^s_{Pu} \end{array}\right] \left[\begin{array}{c} f^c_\tau \\ f^s_{Pr,\tau} \\ f^s_{Pu,\tau} \end{array}\right] + \left[\begin{array}{c} \varepsilon_{Pr,\tau} \\ \varepsilon_{Pu,\tau} \end{array}\right],$$

where factors are

- f^c_τ: latent common $(k^c \times 1)$
- $f^s_{Pe,\tau}$: latent group1-specific $(k^1_s \times 1)$
- $f^s_{Pu,\tau}$: latent group2-specific $(k^2_s \times 1)$

such that:

$$E\left[\begin{array}{c} f^c_\tau \\ f^s_{Pr,\tau} \\ f^s_{Pu,\tau} \end{array}\right] = \left[\begin{array}{c} \mu^c \\ \mu^s_{Pr} \\ \mu^s_{Pu} \end{array}\right], \quad \text{and} \quad V\left[\begin{array}{c} f^c_\tau \\ f^s_{Pr,\tau} \\ f^s_{Pu,\tau} \end{array}\right] = \left[\begin{array}{ccc} I_{k^c} & 0 & 0 \\ 0 & I_{k^s_{Pr}} & \Phi \\ 0 & \Phi' & I_{k^s_{Pu}} \end{array}\right]$$

Key estimation steps

STEP 1: Run PCA on each panel $y_{j,\tau}$

$\Rightarrow$ Estimate pervasive factors $h_{j,\tau}$ in each group $j = Pr, Pu$, and **rotate them to be portfolios of the original returns**

see, e.g., Fama (1974), Connor and Korajczyk (1988), Pukthuanthong, Roll, and Subrahmanyam (2019)

STEP 2: Run canonical correlation analysis of $h_{Pe,\tau}$ and $h_{Pr,\tau}$

$\Rightarrow$ The number of common factors k^c in f^c_τ is equal to the estimated **number of canonical correlations** between $h_{Pe,\tau}$ and $h_{Pr,\tau}$ **equal to 1**

Key estimation steps

STEP 1: Run PCA on each panel $y_{j,\tau}$

$\Rightarrow$ Estimate pervasive factors $h_{j,\tau}$ in each group $j = Pr, Pu$, and **rotate them to be portfolios of the original returns**

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STEP 2: Run canonical correlation analysis of $h_{Pe,\tau}$ and $h_{Pr,\tau}$

$\Rightarrow$ The number of common factors k^c in f^c_τ is equal to the estimated **number of canonical correlations** between $h_{Pe,\tau}$ and $h_{Pr,\tau}$ **equal to 1**

STEP 3: Estimate of common and group-specific factors

- Regress returns $y_{j,\tau}$ on $\hat{f}^c_{j,\tau}$ and $\hat{f}^s_{j,\tau}$ to obtain the loadings matrices

$$\hat{\Lambda}_j = \left[\ \hat{\Lambda}^c_j\ ,\ \hat{\Lambda}^s_j\ \right] \qquad \text{for} \quad j = Pr, Pu$$

- Estimate the common ($\hat{f}^{c*}_{j,\tau}$) and group-specific ($\hat{f}^s_{j,\tau}$) factors by **cross-sectional regressions** at each date τ of the returns $y_{j,\tau}$ in each group j on the loadings $\hat{\Lambda}_j$

Factor-models' performance metrics

- *Total* R^2 of Kelly, Pruitt, and Su (2019):

$$Total\ R_j^2 = 1 - \frac{\sum_{i=1}^{N_j} \sum_{\tau=1}^{T} \left(y_{j,i,\tau} - \hat{\beta}'_{j,i,\tau} f_\tau \right)^2}{\sum_{i=1}^{N_j} \sum_{\tau=1}^{T} y_{j,i,\tau}^2} .$$

  - the fraction of fund return time-series variability explained by the factors
  - aggregated across all periods

Factor-models' performance metrics

- *Total* R^2 of Kelly, Pruitt, and Su (2019):

$$Total\ R_j^2 = 1 - \frac{\sum_{i=1}^{N_j} \sum_{\tau=1}^{T} \left(y_{j,i,\tau} - \hat{\beta}'_{j,i,\tau} f_\tau \right)^2}{\sum_{i=1}^{N_j} \sum_{\tau=1}^{T} y_{j,i,\tau}^2} .$$

  - the fraction of fund return time-series variability explained by the factors
  - aggregated across all periods

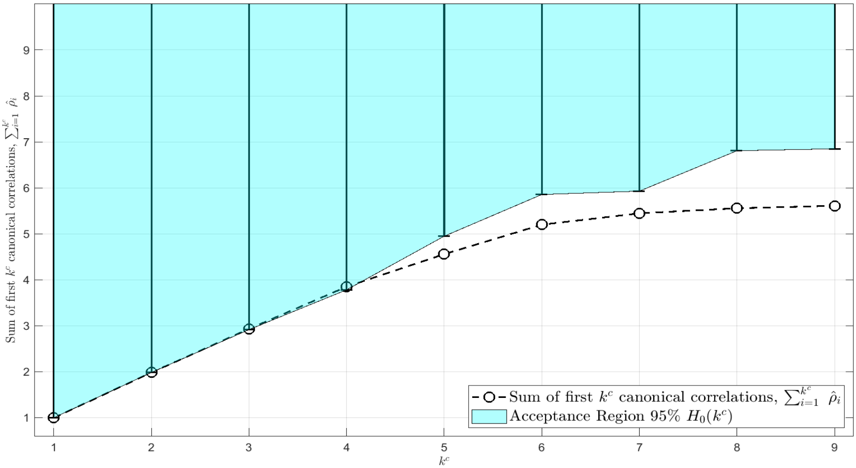
- *Pricing error* of Kelly, Palhares, and Pruitt (2020)

$$\text{Pricing error}_j = \frac{\sum_{i=1}^{N_j} \hat{\alpha}_i^2}{\sum_{i=1}^{N_j} \left(\frac{1}{T} \sum_{\tau=1}^{T} y_{j,i,\tau} \right)^2} , \qquad \text{with } \ \hat{\alpha} = \frac{1}{T} \sum_{t=1}^{T} (y_{j,i,\tau} - \hat{\beta}'_{j,i,\tau} f_\tau).$$

  - a.k.a., "Relative Pricing error R^2"
  - the fraction of the squared unconditional mean excess returns not explained by the factors and their betas
  - similar to (the numerator of) a GRS-like test for the null that the pricing errors for the test assets are zero

How many factors?

following Andreou, Gagliardini, Ghysels, & Rubin (2019)



The figure provides a graphical representation of the test of the number of common factors k^c among 9 principal components from panels of PERs and CARs.

Performance evaluation of factor models

n. of factors	1	2	3	4	5	6	7	8	9
PE returns									
Total R^2									
CF				95.58					
CF+PEF					95.79	96.25	96.77	97.37	98.02
PC	82.28	89.89	94.76	96.18	96.82	97.37	97.68	97.87	98.07
Pricing Error									
CF				6.00					
CF+PEF					5.56	5.05	3.98	3.27	3.06
CA returns									
Total R^2									
Pricing Error									

The pricing errors compare favorably to $\sim$ 11% for size-&style-sorted portfolios in Andreou et al. (2022)

Performance evaluation of factor models

n. of factors	1	2	3	4	5	6	7	8	9
				PE returns					
Total R^2									
CF				95.58					
CF+PEF					95.79	96.25	96.77	97.37	98.02
PC	82.28	89.89	94.76	96.18	96.82	97.37	97.68	97.87	98.07
Pricing Error									
CF				6.00					
CF+PEF					5.56	5.05	3.98	3.27	3.06
				CA returns					
Total R^2									
CF				90.31					
CF+CAF					91.31	92.46	94.75	95.80	96.98
PC	76.84	84.42	88.48	94.02	95.89	97.10	98.01	98.63	98.88
Pricing Error									
CF				6.67					
CF+CAF					5.62	5.66	5.14	5.18	4.10

Higher total R^2 for 4 CFs with PERs than with CARs suggests that nowcasted PE excess returns (or cash flow realizations) co-vary with the common factors!

PE contribution to public equity portfolio performance

	Unconstrained factor weights: any w_f s.t. $\sum_f w_f = 1$						**Non-neg. factor weights:** $w_f \geq 0$			
	No PE factors	PE factors allow short positions in PE funds						**Long-only PE**		No PE factors
		+1 PEFs	+2 PEFs	+3 PEFs	+4 PEFs	+5 PEFs			&3%LP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Controls are 9 PCs from CARs									
Max SR	1.28									1.28
pval ΔMax SR										
PE weight										
$q_{2.5\%}$(PE weight)										
1% of worst DD	5.47									5.47
Min SD	2.42									2.42
	Controls are FF5									
Max SR	1.09									1.01
pval ΔMax SR										
PE weight										
$q_{2.5\%}$(PE weight)										
1% of worst DD	7.84									8.54
Min SD	3.54									3.62

SR: Sharpe-ratio **DD**: bootstrapped cum.loss for Max SR portf. **Min SD**: St.Dev. of the GMV portf.

PE contribution to public equity portfolio performance

	Unconstrained factor weights: any w_f s.t. $\sum_f w_f = 1$							Non-neg. factor weights: $w_f \geq 0$		
	No PE factors	PE factors allow short positions in PE funds						Long-only PE		No PE factors
		+1 PEFs	+2 PEFs	+3 PEFs	+4 PEFs		+5 PEFs		&3%LP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Controls are 9 PCs from CARs										
Max SR	1.28	1.88	2.35	2.44	2.52	2.54	2.54			1.28
pval ΔMax SR		(0.01)	(0.01)	(0.30)	(0.32)	(0.78)	[0.00]			
PE weight		0.54	0.66	0.72	0.76	0.78	0.77			
$q_{2.5\%}$(PE weight)		0.41	0.59	0.63	0.67	0.68	0.41			
1% of worst DD	5.47	2.15	1.73	1.89	1.54	1.67	1.66			5.47
Min SD	2.42	1.47	1.23	1.17	1.14	1.08	1.08			2.42
Controls are FF5										
Max SR	1.09	1.78	2.09	2.32	2.46	2.47	2.45			1.01
pval ΔMax SR		(0.00)	(0.06)	(0.13)	(0.15)	(0.85)	[0.00]			
PE weight		0.65	0.78	0.86	0.90	0.91	0.88			
$q_{2.5\%}$(PE weight)		0.51	0.67	0.76	0.81	0.82	0.82			
1% of worst DD	7.84	2.90	2.35	2.16	1.72	1.76	1.69			8.54
Min SD	3.54	1.93	1.68	1.40	1.34	1.19	1.20			3.62

(p-value for equality with value to the left) [p-value for equality with the value in col.#1]

PE contribution to public equity portfolio performance

	Unconstrained factor weights: any w_f s.t. $\sum_f w_f = 1$							Non-neg. factor weights: $w_f \geq 0$		
	No PE factors	PE factors allow short positions in PE funds						Long-only PE		No PE factors
		+1 PEFs	+2 PEFs	+3 PEFs	+4 PEFs		+5 PEFs		&3%LP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Controls are 9 PCs from CARs										
Max SR	1.28	1.88	2.35	2.44	2.52	2.54	2.54	1.40		1.28
pval ΔMax SR		(0.01)	(0.01)	(0.30)	(0.32)	(0.78)	[0.00]	[0.00]		
PE weight		0.54	0.66	0.72	0.76	0.78	0.77	0.21		
$q_{2.5\%}$(PE weight)		0.41	0.59	0.63	0.67	0.68	0.41	0.11		
1% of worst DD	5.47	2.15	1.73	1.89	1.54	1.67	1.66	5.26		5.47
Min SD	2.42	1.47	1.23	1.17	1.14	1.08	1.08	2.37		2.42
Controls are FF5										
Max SR	1.09	1.78	2.09	2.32	2.46	2.47	2.45	1.28		1.01
pval ΔMax SR		(0.00)	(0.06)	(0.13)	(0.15)	(0.85)	[0.00]	[0.02]		
PE weight		0.65	0.78	0.86	0.90	0.91	0.88	0.39		
$q_{2.5\%}$(PE weight)		0.51	0.67	0.76	0.81	0.82	0.82	0.21		
1% of worst DD	7.84	2.90	2.35	2.16	1.72	1.76	1.69	7.39		8.54
Min SD	3.54	1.93	1.68	1.40	1.34	1.19	1.20	3.29		3.62

(p-value for equality with value to the left) [p-value for equality with the value in col.#1]

PE contribution to public equity portfolio performance

	Unconstrained factor weights: any w_f s.t. $\sum_f w_f = 1$							Non-neg. factor weights: $w_f \geq 0$		
	No PE factors	PE factors allow short positions in PE funds						Long-only PE		No PE factors
		+1 PEFs	+2 PEFs	+3 PEFs	+4 PEFs	+5 PEFs			&3%LP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Controls are 9 PCs from CARs										
Max SR	1.28	1.88	2.35	2.44	2.52	2.54	2.54	1.40	1.30	1.28
pval ΔMax SR		(0.01)	(0.01)	(0.30)	(0.32)	(0.78)	[0.00]	[0.00]	[0.41]	
PE weight		0.54	0.66	0.72	0.76	0.78	0.77	0.21	0.18	
$q_{2.5\%}$(PE weight)		0.41	0.59	0.63	0.67	0.68	0.41	0.11	0.00	
1% of worst DD	5.47	2.15	1.73	1.89	1.54	1.67	1.66	5.26	5.19	5.47
Min SD	2.42	1.47	1.23	1.17	1.14	1.08	1.08	2.37	2.37	2.42
Controls are FF5										
Max SR	1.09	1.78	2.09	2.32	2.46	2.47	2.45	1.28	1.11	1.01
pval ΔMax SR		(0.00)	(0.06)	(0.13)	(0.15)	(0.85)	[0.00]	[0.02]	[0.74]	
PE weight		0.65	0.78	0.86	0.90	0.91	0.88	0.39	0.37	
$q_{2.5\%}$(PE weight)		0.51	0.67	0.76	0.81	0.82	0.82	0.21	0.20	
1% of worst DD	7.84	2.90	2.35	2.16	1.72	1.76	1.69	7.39	7.66	8.54
Min SD	3.54	1.93	1.68	1.40	1.34	1.19	1.20	3.29	3.29	3.62

A long-only PE adds significant value nonetheless, but may not compensate for illiquidity!

PE contribution to public equity portfolio performance

	Unconstrained factor weights: any w_f s.t. $\sum_f w_f = 1$							Non-neg. factor weights: $w_f \geq 0$		
	No PE factors	PE factors allow short positions in PE funds						Long-only PE		No PE factors
		+1 PEFs	+2 PEFs	+3 PEFs	+4 PEFs	+5 PEFs			&3%LP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Controls are 9 PCs from CARs										
Max SR	1.28	1.88	2.35	2.44	2.52	2.54	2.54	1.40	1.30	1.28
pval ΔMax SR		(0.01)	(0.01)	(0.30)	(0.32)	(0.78)	[0.00]	[0.00]	[0.41]	
PE weight		0.54	0.66	0.72	0.76	0.78	0.77	0.21	0.18	
$q_{2.5\%}$(PE weight)		0.41	0.59	0.63	0.67	0.68	0.41	0.11	0.00	
1% of worst DD	5.47	2.15	1.73	1.89	1.54	1.67	1.66	5.26	5.19	5.47
Min SD	2.42	1.47	1.23	1.17	1.14	1.08	1.08	2.37	2.37	2.42
Controls are 9 PCs from the Equity Zoo										
Max SR	1.22	1.78	2.06	2.26	2.42	2.43	2.40	1.45	1.24	1.19
pval ΔMax SR		(0.01)	(0.08)	(0.15)	(0.11)	(0.79)	[0.00]	[0.00]	[0.77]	
PE weight		0.58	0.84	0.85	0.91	0.92	0.87	0.40	0.35	
$q_{2.5\%}$(PE weight)		0.40	0.62	0.69	0.77	0.77	0.40	0.24	0.00	
1% of worst DD	6.54	2.85	2.44	2.12	1.62	1.70	1.70	5.39	5.49	5.62
Min SD	2.01	1.53	1.47	1.24	1.21	1.08	1.09	1.99	1.99	2.01

A long-only PE adds significant value nonetheless, but may not compensate for illiquidity!

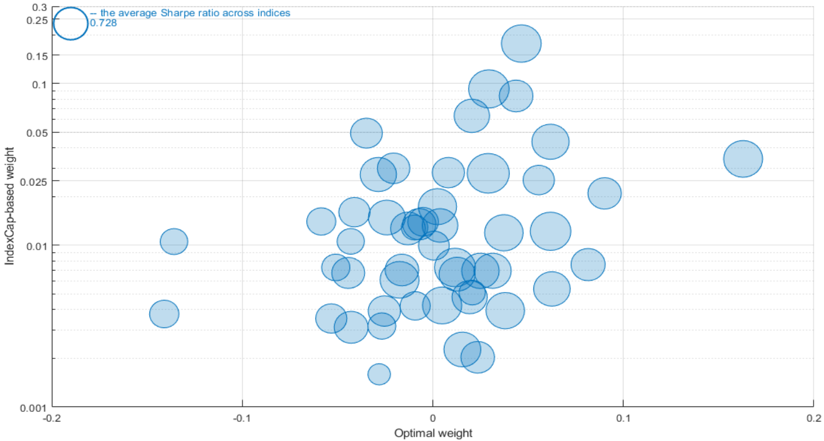
Optimal index weights

implied by optimal PE-specific factors weights

	PEF 1	PEFs 1-2	PEFs 1-3	PEFs 1-4	PEFs 1-5
Largest and smallest port. weights					
Largest 1	L/RE(0.11)	Grw/Fin(0.13)	Buyout/IT(0.14)	Buyout/IT(0.16)	Buyout/IT(0.16)
Largest 2	Buyout/Fin(0.08)	Buyout/Fin(0.12)	Buyout/Fin(0.08)	L/ElyStgVC/Gen(0.09)	L/ElyStgVC/Gen(0.09)
Largest 3	Infra/Gen(0.08)	Buyout/IT(0.12)	L/ElyStgVC/Gen(0.08)	Grw/Hlth(0.08)	Grw/Hlth(0.08)
Largest 4	M/RE(0.08)	L/ElyStgVC/Gen(0.08)	Grw/Hlth(0.08)	L/Distres(0.06)	S/Buyout/Cons(0.06)
Largest 5	S/RE(0.06)	Grw/Hlth(0.08)	S/Buyout/Cons(0.06)	Buyout/Fin(0.06)	Buyout/Fin(0.06)
Largest 6	L/Buyout/Gen(0.06)	Infra/Gen(0.06)	Infra/Gen(0.06)	Infra/Gen(0.06)	Infra/Gen(0.06)
Largest 7	Grw/Hlth(0.06)	L/RE(0.05)	L/RE(0.06)	L/Buyout/Gen(0.05)	L/Distres(0.06)
Largest 8	S/Buyout/Gen(0.05)	S/Buyout/Cons(0.05)	L/Distres(0.06)	L/RE(0.05)	L/Buyout/Gen(0.05)
Largest 9	Grw/Fin(0.04)	L/Distres(0.05)	Grw/Fin(0.06)	S/Buyout/Cons(0.04)	L/RE(0.04)
Largest 10	L/ElyStgVC/Gen(0.04)	L/Buyout/Gen(0.04)	L/Buyout/Gen(0.05)	M/Buyout/HD(0.04)	M/Buyout/Ind(0.04)
Smallest 1	NatRes/Gen(−0.22)	NatRes/Gen(−0.18)	NatRes/Gen(−0.15)	NatRes/Gen(−0.15)	NatRes/Gen(−0.14)
Smallest 2	NatRes/Mat(−0.12)	NatRes/Mat(−0.15)	NatRes/Mat(−0.13)	NatRes/Mat(−0.13)	NatRes/Mat(−0.14)
Smallest 3	L/Buyout/Ind(−0.10)	BalVC/Gen(−0.06)	BalVC/Gen(−0.06)	BalVC/Gen(−0.06)	BalVC/Gen(−0.06)
Smallest 4	S/BalVC/IT(−0.07)	L/Buyout/Ind(−0.05)	L/ElyStgVC/Hlth(−0.05)	L/ElyStgVC/Hlth(−0.05)	S/ElyStgVC/Gen(−0.05)
Smallest 5	BalVC/Hlth(−0.04)	L/ElyStgVC/Hlth(−0.05)	BalVC/Hlth(−0.04)	S/ElyStgVC/Gen(−0.05)	L/ElyStgVC/Hlth(−0.05)
$\sum w_i^{\text{net},k}<0$	(−0.92)	(−.88)	(−0.85)	(−0.88)	(−0.88)
Return characteristics of PE factors					
Sharpe Ratio	1.19	1.66	1.89	2.04	2.09
Inform. Ratio	1.37	1.96	2.07	2.16	2.18
R^2 on CAPC	0.22	0.25	0.15	0.15	0.12

Sharpe and Information ratios are annualized and all significant. The information ratio is computed with the residuals from a regression of each optimal combination of PEFs on 9 PCs of CAs (CAPC)

How do Optimal PER weights related to their 'Index Cap'-based weights?



The correlation is significantly positive, **but only 0.27!**

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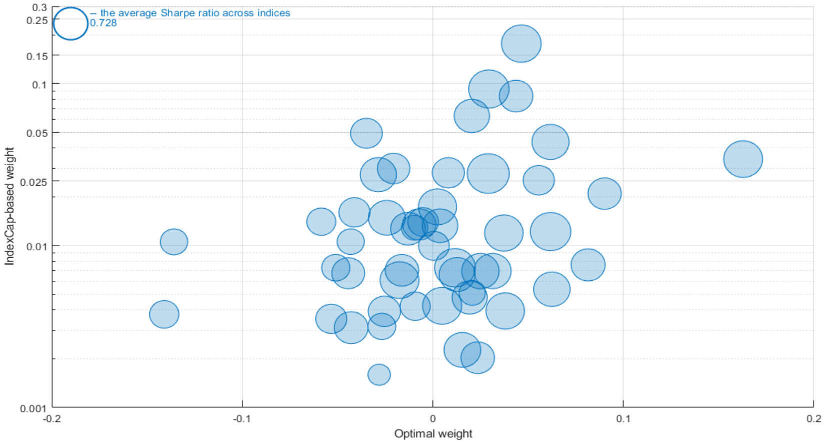
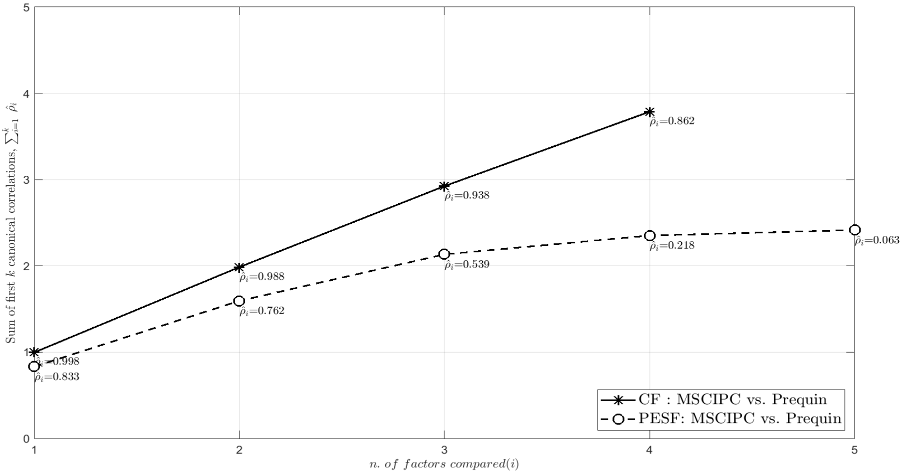


The correlation is significantly positive, **but only 0.27!** **Nonetheless:**

- the maximal SR—at 1.35 with 9 PCs from CARs—is significantly **higher** (lower) than **1.28 with zero** (1.40 with optimal) PE indices' weights
- the 95% confidence interval for the passive PE weight is 6% to 17% (if no liquidity premia)

Do PE fund datasets span one another?



- with regard to common with public equities factors — **Yes**
- with regard to specific to PE factors — **No**

Other results and robustness tests

- Which PE dataset's factors better "price" the other PE dataset?
  - MSCI-Burgiss

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- optimal index-level weights are largely concordant across PE-factor portoflios
  - yet, even the 5th factor add meaningful value (by reducing risk)

New Section (still pending)

What are these PE-specific factors?

- Explore the lead-lag relationship of the PEF returns with:
  - bond yields (level,slope) and credit spreads
  - liquidity factors
  - M& activity levels
  - IPO activity levels and pricing

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- What are the differences in factor loading patterns are by one dimension at a time:
  - fund style (buyout, growth, venture, ...)
  - fund size
  - industry specialty
  - ...

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  - as does the extent active manager selection can help

- Many diversified PE strategies may exhibit relatively unfavorable risk-return profile over at least 21 years