Empirical Asset Pricing: S03
Towards the Factor Zoo

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Structure of the course

- Email: amedeo.andriollo@dauphine.psl.eu
- Grading follows a 30-70 rule: 70% final exam, 30% project/homework.
- Dense slides. References at the end.
- Office hours: feel "free" to (DO) come.
- If you spot any typos/mistake, please let me know: slides are updated regularly.
- This session partially builds on Franzoni's and Koijen's.

⊵ Updates will come.

A Quick Warm Up: Previous Session

- CAPM:

$$r_{i,t} = \alpha_i + \beta_i r_{MKT,t} + \epsilon_{i,t}, \qquad i = 1, ..., N$$

  where, for asset i, $\{r_{i,t}\}$ are the excess returns, $\{\beta_i\}$ mkt betas , $\{\epsilon_{i,t}\}$ idiosyncratic risk, and the $\{\alpha_i\}$ are the pricing errors.
- Mkt portfolio is tradable: $\gamma = \mathbb{E}[r_{MKT,t}] \implies \alpha_i = 0, \quad i = 1, ...N$
- Testing whether CAPM is on the MV frontier: $\mathcal{H}_0 : \alpha_i = 0, \quad i = 1, ..., N$
  ↪ Time Series (TS) or Cross-sectional (XS) tests:
  Gibbons et al. (1989)'s (connection with SR), Fama and MacBeth (1973).
- Rejection $\implies$ Pricing risk not fully spanned by MKT. Puzzle?
  - Look at the XS and TS structure of the α's and ϵ's: "Is the idiosyncratic risk pricing?"
  ↪ : a portfolio whose exp. return is in excess of what can be explained by a benchmark pricing model: i) Mispricing or other frictions, ii) missing pricing factor: $\alpha = \beta_{miss}\gamma_{miss}$

↪ (Empirical) Multifactor model: *"All puzzles are joint puzzles of expected returns and betas. Beta without expected return is just as much a puzzle [...] as expected return without beta"* (Cochrane, 2011)

Risk Premium vs. SDF loading

- In general, suppose we have the following beta-pricing model: (vector form)

$$r_t = \beta\gamma + \beta v_t + u_t, \qquad v_t = f_t - \mathbb{E}[f_t], \quad \mathbb{E}[v_t] = \mathbb{E}[u_t] = \mathbb{E}[v_t u_t'] = 0$$

  with $\{r_t\}$ as $N \times 1$ vector of excess returns, and $\{v_t\}$ as $p \times 1$ innovation of factors $\{f_t\}$.
  $\hookrightarrow$ risk premia of the factors is γ.
- Equivalently, we can write the SDF as: $m_t = 1 - \lambda' v_t$, where λ is the SDF/factor loadings[1].
- By definition of SDF: $\mathbb{E}[m_t r_t] = 0 \iff \mathbb{E}[r_t] - \beta \text{Var}(v_t)\lambda$.
  $\implies \gamma = \text{Var}(v_t)\lambda$.
- Different interpretation of the two objects:
  - Risk premium: "How much are investors willing to pay to hedge this (priced) risk?"
    - Any asset that loads on some priced risk should command a risk premium
  - SDF loadings: "Does this factor help pricing the cross-section of assets?"
    - SDF is prop. to MVE portfolio so λ is prop. to the optimal portfolio weights (tradable).

[1] Previous slides: $M_{t+1} = (1 + R_{f,t+1})^{-1} \left\{1 - (E_t[R^\star_{t+1}]\text{Var}_t[R^\star_{t+1}]^{-1})(R^\star_{t+1} - \mathbb{E}_t[R^\star_{t+1}])\right\}$

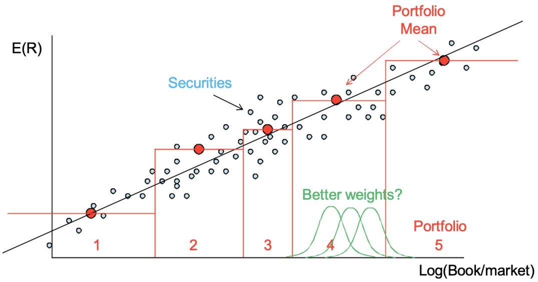
Deviation from CAPM: Size and Value

- Size "puzzle" (Banz, 1981): small firms' stocks associate with higher avg. returns.
  $\hookrightarrow$ long on small mkt cap(italization), and short on big.
- Value "puzzle" (Stattman, 1980): Book-to-Market (B/M) positively related to avg. returns.
  $\hookrightarrow$ long on value (high B/M), and short on growth (low B/M).
- Inspiration for B/M: like D/P but across assets:
  - Previous slides: $p_t - d_t \approx \text{const.} + \mathbb{E}_t[\sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{t+j} - r_{t+j})]$
  - Stocks with high $\mathbb{E}[r_{i,t}]$ (and high betas) will have low $p_t - d_t$, D/P reveals which assets have high/low expected returns by investors.

  $\hookrightarrow$ Low price (=high B/M) stocks associated with high avg. returns
- Fama and French (1992):
  - Findings: mkt betas explains little of XS, and size and B/M are jointly significant.
  - The betas are computed by forming portfolios (see next slide), then Fama and MacBeth (1973)'s reg. of returns onto betas and accounting variables.

$\hookrightarrow$ "Are size and value risk factors?" [suspense]

Portfolio sorting



Portfolios over individual assets? 1) volatility, 2) cond. vs. uncond., 3) measurement errors.

Univariate Sorting:

- B is the number of portfolios (e.g., 25 or 10) and so percentiles for the breakpoints $\{B_k\}$
- At time t, each asset return $r_{i,t}$ is associated with a characteristic $x_{i,t}$.
  Sorting the characteristic $\implies$ characteristic-implied sorting of returns.
- B "bins" of XS avg. (equally or value-weighted) forms the sorted B portfolios: $\bar{R}_{k,t} = \sum_i w_{i,t} R_{i,t} / \sum w_{i,t}, \quad w_{i,t} = \omega_{i,t} \times 1\{B_{k-1,t} \leq x_{i,t} \leq B_{k,t}\}$

About timing/rebalancing:

- *"At the end of each year t, we form [...] portfolios [...] enter into positions [...] as of the close of the last trading day during year t. We hold the portfolios unchanged until the end of year $t+1$, at which point all portfolios are liquidated at the closing prices on the last trading day of year $t+1$. We repeat the procedure for each year t."* Bali et al. (2016)

Fama and French (1993) (1)

- Intro:
  - Starting point is the beta-pricing model: positive RP commands high exp. returns high betas.
    $\hookrightarrow$ when using tradable factors, then we have an estimate of the RP (hist. means).
  - size = mkt capitalization: price x shares; value = B/M: accounting vs. mkt price per share.
- Goal: a unique model that explains returns on stocks and bonds:
  "We expand the set of asset returns to be explained [...] If markets are integrated, a single model should also explain bond returns".
  $\hookrightarrow$ equity factors from Fama and French (1992), and bond factors: default and term premia.
- While Fama and French (1992) uses XS reg, Fama and French (1993) uses TS reg.
- Findings: *"In a nutshell, our results suggest that there are at least three stock-market factors and two term-structure factors in returns."*

$\hookrightarrow$ Main takeaway is the three-factor model for equity.
(From google scholar: 40k citations cumulative in the past 53 years, 2.4k last year)

Fama and French (1993) (2)

- From the Fama and French (1992)'s economic motivation to pricing:
  - Size: *"Small firms can suffer a long earnings depression that bypasses big firms suggests that size is associated with a common risk factor that might explain the negative relation between size and average return."*
  - Value: *"The relation between book-to-market equity and earnings suggests that relative profitability is the source of a common risk factor in returns that might explain the positive relation between BE/ME and average return."*
- Add two (tradable) factors: SMB ("*small minus big*"), HML ("*high minus low*").
  - In June of year t, portfolios are built. Monthly Value-Weighted returns are calculated from July t to June $t+1$. Portfolios are then reformed in June $t+1$. B/M is measured in December $t-1$.
  - VW: $\omega_{i,t} = \text{mkt cap}_{i,t} / \sum_i^{bin} \text{mkt cap}_{i,t}$

↪ *"True mimicking portfolios for the common risk factors in returns minimize the variance of firm-specific factors.[...] Using value-weighted components is in the spirit of minimizing variance, since return variances are negatively related to size [...] results in mimicking portfolios that capture the different return behaviors of small and big stocks [...] in a way that corresponds to realistic investment opportunities."*

Fama and French (1993) (3)

- Add two (tradable) factors: SMB (*"small minus big"*), HML (*"high minus low"*).
  - Sort independently by ME and BE/ME, to get 6 VW portfolios:
    - *"Median NYSE size is then used to split NYSE, Amex, and (after 1972) NASDAQ stocks into two groups. small and big (S and B)".*
    - *"Three book-to-market equity groups based on the breakpoints for the bottom 30% (Low), middle 40% (Medium) and top 30% (High) of the ranked values of BE/ME for NYSE stocks."*

	Low	Medium	High
Big	LB	MB	HB
Small	LS	MS	HS

  - $SMB = (LS - LB)/3 + (MS - MB)/3 + (HS - HB)/3$ (size: long-short rows).
  - $HML = (HS - LS)/2 + (HB - LB)/2$ (value: long-short columns).
- These are factors that price (RHS): which assets (LHS)? $5 \times 5 = 25$ VW portfolios:

$\hookrightarrow$ *"We construct 25 portfolios from the intersections of the size and BE/ME quintiles and calculate value-weighted monthly returns on the portfolios from July off to June of $t+1$."*

Fama and French (1993) (4)

- Long-short portfolios (factors) to explain (price) size and B/M portfolios (assets). Tautology?
  - Form portfolios by stock's first letter (Apple,..., Tesla).
  - Form a zero-investment portfolio: long (A-M), short (N-Z), call it $\tilde{f}_t$.
  - Significant beta on this portfolio emerges if there is a common factor:

$$r_{i,t} = \beta_i f_t + u_{i,t}, \quad \mathbb{E}[u_{i,t}] = \text{Cov}(f_t, u_{i,t}) = 0$$

  with: $\mathbb{E}[u_{i,t} u_{j,t}] = 0 + \sigma_u^2 1\{i = j\}$, $\mathbb{E}[f_t] = \sigma_f^2$.

  - Then:

$$\begin{aligned}
\text{Cov}\left(r_{i,t}, \tilde{f}_t\right) &= \text{Cov}\left(\beta_i f_t + u_{i,t}, \left(\frac{\sum_{i_1} \tilde{\beta}_{i_1}}{N_1} - \frac{\sum_{i_2} \tilde{\beta}_{i_2}}{N_2}\right) f_t + (\bar{u}^{(1)} - \bar{u}^{(2)})\right) \\
&= \beta_i \left(\frac{\sum_{i_1} \tilde{\beta}_{i_1}}{N_1} - \frac{\sum_{i_2} \tilde{\beta}_{i_2}}{N_2}\right) \sigma_f^2 + \frac{1}{N_i} \sigma_u^2 \\
&\approx \beta_i \times \text{beta-spread} \times \sigma_f^2
\end{aligned}$$

  - When is the beta spread ≈ 0?
  - Recall that Fama and MacBeth (1973)'s regression of returns onto characteristic can be interpreted as long-short portfolio.

Fama and French (1993) (5)

Table 4

Regressions of excess stock and bond returns (in percent) on the excess stock-market return, $RM-RF$: July 1963 to December 1991, 342 months.[a]

$$R(t) - RF(t) = a + b[RM(t) - RF(t)] + e(t)$$

Dependent variable: Excess returns on 25 stock portfolios formed on size and book-to-market equity

Size quintile	Low	2	3	4	High	Low	2	3	4	High
	Book-to-market equity (BE/ME) quintiles									
	b					$t(b)$				
Small	1.40	1.26	1.14	1.06	1.08	26.33	28.12	27.01	25.03	23.01
2	1.42	1.25	1.12	1.02	1.13	35.76	35.56	33.12	33.14	29.04
3	1.36	1.15	1.04	0.96	1.08	42.98	42.52	37.50	35.81	31.16
4	1.24	1.14	1.03	0.98	1.10	51.67	55.12	46.96	37.00	32.76
Big	1.03	0.99	0.89	0.84	0.89	51.92	61.51	43.03	35.96	27.75
	R^2					$s(e)$				
Small	0.67	0.70	0.68	0.65	0.61	4.46	3.76	3.55	3.56	3.92
2	0.79	0.79	0.76	0.76	0.71	3.34	2.96	2.85	2.59	3.25
3	0.84	0.84	0.80	0.79	0.74	2.65	2.28	2.33	2.26	2.90
4	0.89	0.90	0.87	0.80	0.76	2.01	1.73	1.84	2.21	2.83
Big	0.89	0.92	0.84	0.79	0.69	1.66	1.35	1.73	1.95	2.69

- Looking at the TS R^2 (blue):
  - CAPM is doing well for big stocks: the systematic risk accounts for 90%.
  - For small and value stocks, there is more unaccounted risk ($\sim 60\%$).
- Looking at the betas (orange):
  - Larger betas: big and growth stocks.
- Looking at the avg returns: (in their Table 2)
  - Small larger than Big (especially for Value).
  - Value larger than Growth.

↪ Monotonically.

Fama and French (1993) (6)

Table 6

Regressions of excess stock and bond returns (in percent) on the excess market return ($RM-RF$) and the mimicking returns for the size (SMB) and book-to-market equity (HML) factors: July 1963 to December 1991, 342 months.[a]

$$R(t) - RF(t) = a + b[RM(t) - RF(t)] + sSMB(t) + hHML(t) + e(t)$$

Dependent variable: Excess returns on 25 stock portfolios formed on size and book-to-market equity

Book-to-market equity (BE/ME) quintiles

Size quintile	Low	2	3	4	High	Low	2	3	4	High
			b					$t(b)$		
Small	1.04	1.02	0.95	0.91	0.96	39.37	51.80	60.44	59.73	57.89
2	1.11	1.06	1.00	0.97	1.09	52.49	61.18	55.88	61.54	65.52
3	1.12	1.02	0.98	0.97	1.09	56.88	53.17	50.78	54.38	52.52
4	1.07	1.08	1.04	1.05	1.18	53.94	53.51	51.21	47.09	46.10
Big	0.96	1.02	0.98	0.99	1.06	60.93	56.76	46.57	53.87	38.61
			s					$t(s)$		
Small	1.46	1.26	1.19	1.17	1.23	37.92	44.11	52.03	52.85	50.97
2	1.00	0.98	0.88	0.73	0.89	32.73	38.79	34.03	31.66	36.78
3	0.76	0.65	0.60	0.48	0.66	26.40	23.39	21.23	18.62	21.91
4	0.37	0.33	0.29	0.24	0.41	12.73	11.11	9.81	7.38	11.01
Big	−0.17	−0.12	−0.23	−0.17	−0.05	−7.18	−4.51	−7.58	−6.27	−1.18
			h					$t(h)$		
Small	−0.29	0.08	0.26	0.40	0.62	−6.47	2.35	9.66	15.53	22.24
2	−0.52	0.01	0.26	0.46	0.70	−14.57	0.41	8.56	17.24	24.80
3	−0.38	−0.00	0.32	0.51	0.68	−11.26	−0.05	9.75	16.88	19.39
4	−0.42	0.04	0.30	0.56	0.74	−12.51	1.04	8.83	14.84	17.09
Big	−0.46	0.00	0.21	0.57	0.76	−17.03	0.09	5.80	18.34	16.24

- Mkt betas are stat. significant and ≈ 1.
- *"SMB [...] clearly captures shared variation in stock returns that is missed by the market and by HML. Moreover, the slopes on SMB for stocks are related to size. In every book-to-market quintile, the slopes on SMB decrease monotonically from smaller- to bigger-size quintiles [...] Similarly, the slopes on HML [...] are systematically related to BE/ME."*
- *"For the five portfolios in the smallest-size quintile, R^2 increases from values between 0.61 and 0.70 in table 4 to values between 0.94 and 0.97 in table 6."*

↪ Covariation: sources of priced risk.

Fama and French (1993) (7)

Table I—*Continued*

	Book-to-Market Equity (BE/ME) Quintiles									
Size	Low	2	3	4	High	Low	2	3	4	High
Panel B: Regressions: $R_i - R_f = a_i + b_i(R_M - R_f) + s_i SMB + h_i HML + e_i$										
	a					t(a)				
Small	−0.45	−0.16	−0.05	0.04	0.02	−4.19	−2.04	−0.82	0.69	0.29
2	−0.07	−0.04	0.09	0.07	0.03	−0.80	−0.59	1.33	1.13	0.51
3	−0.08	0.04	−0.00	0.06	0.07	−1.07	0.47	−0.06	0.88	0.89
4	0.14	−0.19	−0.06	0.02	0.06	1.74	−2.43	−0.73	0.27	0.59
Big	0.20	−0.04	−0.10	−0.08	−0.14	3.14	−0.52	−1.23	−1.07	−1.17
	b					t(b)				
Small	1.03	1.01	0.94	0.89	0.94	39.10	50.89	59.93	58.47	57.71
2	1.10	1.04	0.99	0.97	1.08	52.94	61.14	58.17	62.97	65.58
3	1.10	1.02	0.98	0.97	1.07	57.08	55.49	53.11	55.96	52.37
4	1.07	1.07	1.05	1.03	1.18	54.77	54.48	51.79	45.76	46.27
Big	0.96	1.02	0.98	0.99	1.07	60.25	57.77	47.03	53.25	37.18
	s					t(s)				
Small	1.47	1.27	1.18	1.17	1.23	39.01	44.48	52.26	53.82	52.65
2	1.01	0.97	0.88	0.73	0.90	34.10	39.94	36.19	32.92	38.17

- Table I is from Fama and French (1996)
- *"At a minimum, the available evidence suggests that the three-factor model [...], with intercepts [...] equal to 0.0, is a parsimonious description of returns and average returns."*
- "Returns": high R^2 (variation over TS), "average returns": small alphas (variations over XS).

↪ TS R^2 tells us how much is strong the factor structure in the 25 portfolios.

- GRS rejects the model but *"This rejection of the three-factor model is testimony to the explanatory power of the regressions."*

↪ *"the glass is 90% full: this is a pretty darn good model"* [Cochrane]

Fama and French (1993) (8)

- Back-up story: aggregate distress risk. Liew and Vassalou (2000):
  - *"HML and SMB portfolios are related to future growth in the real economy [...] They act as state variables in the context of Merton's (1973) intertemporal capital asset pricing model (ICAPM)."*
- Fama and French (1993)'s viewpoint is that their model supports rational pricing:
  - Since CAPM fails to explain average returns, then there are arbitrage opportunities aside mkt

  ↪ However, if no arbitrage and common patterns in the TS and XS implies there must be additional factors spanning returns: gold rush to find factors.
- The contribution is a three-factor model that explains the other anomalies/puzzles: new SDF benchmark after CAPM (working across several asset classes).
- What about size and value factors after the 90's? In the last decade:
  - SMB has not done well: annualized return of 2.7% (Dec.1926-2009) vs. -0.2% (Jan.2010-20).
  - HML has done very poorly: annu. return of 5.1% (Dec.1926-2009) vs. -5.6% (Jan.2010-20).

Sorting on Past Returns: (LT) Reversal (1)

- Value puzzle can be rationalized by overreaction: bad news lead to low price and high B/M.
  - *"Companies with very low P/E's are thought to be temporarily "undervalued" because investors become excessively pessimistic after a series of bad earnings reports or other bad news. Once future earnings turn out to be better than the unreasonably gloomy forecasts, the price adjusts."* (De Bondt and Thaler, 1985)
  - ↪ *"If stock prices systematically overshoot, then their reversal should be predictable from past return data alone [...] Specifically, two hypotheses are suggested: (1) Extreme movements in stock prices will be followed by subsequent price movements in the opposite direction. (2) The more extreme the initial price movement, the greater will be the subsequent adjustment. "*(De Bondt and Thaler, 1985)
- How they build the portfolios?
  1. Collect the CAPM residuals.
  2. Compute the cumulative returns for the prior 36 months (3y).
  3. Rank them from high to bottom, and consider top/bottom 35 stocks: Winner/Loser portfolios.
  4. The updating of portfolios is done w/out overlapping.
- Having the W and L portfolios, De Bondt and Thaler (1985) calculate the cumulative avg. returns and study the difference.

Sorting on Past Returns: (LT) Reversal (2)

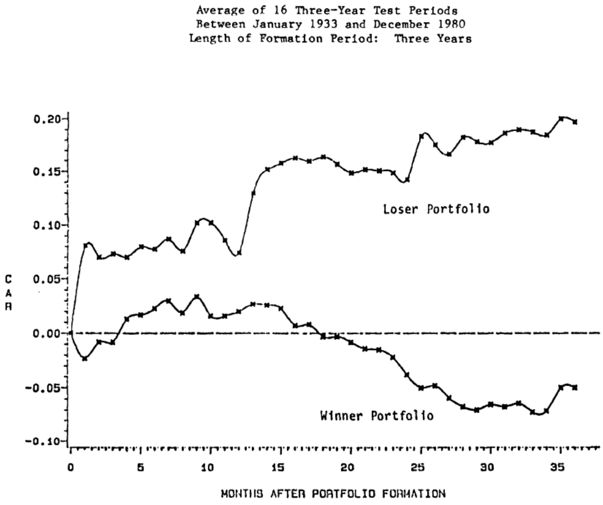


Figure 1. Cumulative Average Residuals for Winner and Loser Portfolios of 35 Stocks (1–36 months into the test period)

- *" Table I confirms the prediction of the overreaction hypothesis. As the cumulative average residuals (during the formation period) for various sets of winner and loser portfolios grow larger, so do the subsequent price reversal"*
- The overreaction is asymmetric: larger for L than for W.
- Robust to:
  - Years for portfolio formation.
  - How residualized is the CAPM.
  - Number of winners/losers.
- The overreaction phenomenon is different from Jan. (or seasonality) effect.
  However, *"long-term losers outperform the long-term winners only in Januaries"* (Jegadeesh and Titman, 1993)
- [What about LT reversal after the 90's?]

Sorting on Past Returns: Momentum (1)

- Copernican revolution: from "long losers short winners" to "long winners short losers":
  " Although the current academic debate has focused on contrarian rather than relative strength trading rules, a number of practitioners still use relative strength" (Jegadeesh and Titman, 1993)

↪ *"This paper provides an analysis of relative strength trading strategies over 3- to 12-month horizons. [...] The profits are not due to the systematic risk of the trading strategies. In addition, the evidence indicates that the profits cannot be attributed to a lead-lag effect resulting from delayed stock price reactions to information about a common factor [...] The evidence is, however, consistent with delayed price reactions to firm-specific information."* (Jegadeesh and Titman, 1993)

- Momentum strategy: in each month, buy (sell) W (L) stocks (in the past 3-12 months, skipping one) and hold them for the next 3-12 months: $\mathbb{E}[r_{i,t} - \bar{r}_t | r_{i,t-1} - \bar{r}_{t-1} > 0] > 0$.
- Single-factor model: $\mathbb{E}[(r_{i,t} - \bar{r}_t)(r_{i,t-1} - \bar{r}_{t-1})] = \sigma_\mu^2 + \sigma_\beta^2 \text{Cov}(f_t, f_{t-1}) + \overline{\text{Cov}}_i(e_{i,t}, e_{i,t-1})$.
  1. XS dispersion in expected returns.
  2. Factor timing: relative strength strategy pick stocks w high β's when high cond. expectation.
  3. Avg. idiosyncratic TS covariance.

Sorting on Past Returns: Momentum (2)

Table I

Returns of Relative Strength Portfolios

The relative strength portfolios are formed based on J-month lagged returns and held for K months. The values of J and K for the different strategies are indicated in the first column and row, respectively. The stocks are ranked in ascending order on the basis of J-month lagged returns and an equally weighted portfolio of stocks in the lowest past return decile is the *sell* portfolio and an equally weighted portfolio of the stocks in the highest return decile is the *buy* portfolio. The average monthly returns of these portfolios are presented in this table. The relative strength portfolios in Panel A are formed immediately after the lagged returns are measured for the purpose of portfolio formation. The relative strength portfolios in Panel B are formed 1 week after the lagged returns used for forming these portfolios are measured. The t-statistics are reported in parentheses. The sample period is January 1965 to December 1989.

		Panel A				Panel B			
J	$K =$	3	6	9	12	3	6	9	12
3	Sell	0.0108	0.0091	0.0092	0.0087	0.0083	0.0079	0.0084	0.0083
		(2.16)	(1.87)	(1.92)	(1.87)	(1.67)	(1.64)	(1.77)	(1.79)
3	Buy	0.0140	0.0149	0.0152	.0156	0.0156	0.0158	0.0158	0.0160
		(3.57)	(3.78)	(3.83)	(3.89)	(3.95)	(3.98)	(3.96)	(3.98)
3	Buy-sell	0.0032	0.0058	0.0061	0.0069	0.0073	0.0078	0.0074	0.0077
		(1.10)	(2.29)	(2.69)	(3.53)	(2.61)	(3.16)	(3.36)	(4.00)
6	Sell	0.0087	0.0079	0.0072	0.0080	0.0066	0.0068	0.0067	0.0076
		(1.67)	(1.56)	(1.48)	(1.66)	(1.28)	(1.35)	(1.38)	(1.58)
6	Buy	0.0171	0.0174	0.0174	0.0166	0.0179	0.0178	0.0175	0.0166
		(4.28)	(4.33)	(4.31)	(4.13)	(4.47)	(4.41)	(4.32)	(4.13)
6	Buy-sell	0.0084	0.0095	0.0102	0.0086	0.0114	0.0110	0.0108	0.0090
		(2.44)	(3.07)	(3.76)	(3.36)	(3.37)	(3.61)	(4.01)	(3.54)

- XS anomaly/factor, not explained by Fama and French (1993)'s model. (Fama and French, 1996).

↪ Momentum + FF3 = Carhart (1997)'s four-factor model.

- Korajczyk and Sadka (2004): Momentum survives after transaction costs (liquidity-weighted strategy).
- Momentum crashes in crisis states (e.g. 2009): when the mkt turns around the low beta stocks (winners) become losers. (Daniel and Moskowitz, 2016)
- What about momentum after the 90's? Still kicking: annualized return of 8.4% (Dec.1926-2009) vs. 4.1% (Jan.2010-20). And exists internationally in most large mkts.

Sorting on Past Returns: Momentum (3)

- "Momentum appears to violate the efficient market hypothesis in its weakest form" (Ehsani and Linnainmaa, 2022)
- What is driving momentum? (Jegadeesh and Titman, 2011)
  - From data:
    - Serial correlation of factor returns is unlikely to have a positive effect on momentum profits.
    - Lead-lag effect to momentum profits depends on the relation between contemporaneous betas and lagged betas: "if the market moves up, high beta stocks will increase more than low beta stocks, but not by as much as they should" (Jegadeesh and Titman, 2011).

    ↪ Jegadeesh and Titman (1993) shows that more profitable when the ranking period and holding period are not contiguous.
  - From (behavioural) theory:
    - Conservatism bias: investors tend to underweight new information when they update their priors. [underreaction]
    - Disposition/Anchoring effect: loss-averse investors tend to hold on to their past losers and sell their past winners. [underreaction]
    - Hot Hand Fallacy [overreaction], Self-attribution bias [overreaction],...
  - Momentum profits are higher for:
    - Growth stocks than value.
    - Higher revenue volatility and lower costs of goods sold.
    - Greater turnover,...

Sorting on Aggregate Liquidity (1)

- Pástor and Stambaugh (2003)'s hypothesis: *"Any investor who employs some form of leverage [...] must liquidate some assets to raise cash. If he holds assets with higher sensitivities to liquidity, then such liquidations are more likely to occur when liquidity is low, since drops in his overall wealth are then more likely to accompany drops in liquidity."*
- Measuring *"trade large quantities quickly, at low cost, and without moving the price"*?

$\hookrightarrow$ Signed volume as proxy of order flow interacting with prices changes.

- Volume-related return reversals (Campbell et al., 1993): *"lower liquidity is reflected in a greater tendency for order flow in a given direction on day d to be followed by a price change in the opposite direction on day $d+1$. [...] returns accompanied by high volume tend to be reversed more strongly [...] consistent with a model in which some investors are compensated for accommodating the liquidity demands of others."*
  $\hookrightarrow$ risk-averse market makers accommodate order flow from liquidity-motivated traders.

Sorting on Aggregate Liquidity (2)

- Breaking it down to its estimation:
  1. Liquidity can be understood as the slope of the demand curve.
     HW: Less liquid markets, demand is more or less elastic?
  2. Trades move prices temporarily: daily price fluctuations associated with order flow.

$$r_{i,d+1,t} - r_{m,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \overbrace{\gamma_{i,t}}^{\text{liquidity}} \text{sign}[r_{i,d,t} - r_{m,d,t}] \cdot v_{i,d,t} + \epsilon_{i,d+1,t}$$

  At day d in month t, $\{r_{i,d,t}\}$ is the return on stock i and its dollar value is $\{v_{i,d,t}\}$, while $\{r_{m,d,t}\}$ is the return on the CRS value-weighted market return.

- $\{\gamma_{i,t}\}$ measures how price changes relate to trading the previous period: *"volume signed by the contemporaneous return [...], should be accompanied by a return that one expects to be partially reversed in the future if the stock is not perfectly liquid [...] one would expect $\{\gamma_{i,t}\}$ to be negative in general and larger in absolute magnitude when liquidity is lower."*

Sorting on Aggregate Liquidity (3)

- $\{\gamma_{i,t}\}$ is not yet a measure of unanticipated innovations.

$\hookrightarrow$ Two problems:

1. The series has a trend and scale (total dollar value of the mkt): *"we first difference and then scale"* and so aggregating it at market level: $\Delta\widehat{\gamma}_t = \frac{m_t}{m_1}\frac{1}{N}\sum_{i=1}^{N}(\widehat{\gamma}_{i,t} - \widehat{\gamma}_{i,t-1})$
2. We need to extract the surprise:

$$\Delta\widehat{\gamma}_t = \beta_0 + \beta_1\Delta\widehat{\gamma}_{t-1} + \beta_2\frac{m_t}{m_1}\widehat{\gamma}_{i,t-1} + u_t$$

$\hookrightarrow$ $\{\mathcal{L}_t = u_t/100\}$ is the innovation in liquidity. **HW:** $+$ive u_t is a $+$ive/-ive liquidity shock?

- Pástor and Stambaugh (2003)'s liquidity factor $+$ FF3:

$$r_{i,t} = \alpha_i + \beta_i^{MKT}MKT_t + \beta_i^{SMB}SMB_t + \beta_i^{HML}HML_t + \beta_i^{LIQ}\mathcal{L}_t + \epsilon_{i,t}$$

$\hookrightarrow$ To form portfolios and look at Postranking Portfolio Betas: project the β_i^{LIQ} onto some characteristics.

Sorting on Aggregate Liquidity (4)

TABLE 4
ALPHAS OF VALUE-WEIGHTED PORTFOLIOS SORTED ON PREDICTED LIQUIDITY BETAS

	Decile Portfolio										
	1	2	3	4	5	6	7	8	9	10	10–1
A. January 1966–December 1999											
CAPM alpha	−5.16	−1.88	−.66	−.07	−1.48	1.48	1.22	1.38	1.68	1.24	6.40
	(−2.57)	(−1.24)	(−.56)	(−.08)	(−1.80)	(1.93)	(1.52)	(1.72)	(1.93)	(1.01)	(2.54)
Fama-French alpha	−6.05	−3.36	−2.15	−1.23	−2.10	.78	.86	1.41	1.90	3.18	9.23
	(−3.77)	(−2.47)	(−1.93)	(−1.37)	(−2.61)	(1.08)	(1.11)	(1.76)	(2.22)	(2.82)	(4.29)
Four-factor alpha	−5.11	−1.66	−1.02	−.76	−1.61	.91	.76	1.55	1.34	2.36	7.48
	(−3.12)	(−1.23)	(−.91)	(−.83)	(−1.96)	(1.22)	(.96)	(1.88)	(1.54)	(2.06)	(3.42)
B. January 1966–December 1982											
CAPM alpha	−2.26	1.63	.54	.67	−3.09	1.44	.61	1.78	1.43	−.93	1.34
	(−.81)	(.76)	(.31)	(.50)	(−2.69)	(1.29)	(.54)	(1.46)	(1.14)	(−.52)	(.36)
Fama-French alpha	−7.32	−2.22	−1.80	−.75	−3.29	1.03	.20	1.91	2.32	1.18	8.50
	(−3.36)	(−1.23)	(−1.13)	(−.59)	(−2.85)	(.95)	(.17)	(1.56)	(1.86)	(.71)	(2.77)
Four-factor alpha	−6.43	−.25	−.22	−.03	−2.46	1.09	.31	2.89	1.67	−.22	6.21
	(−2.82)	(−.13)	(−.13)	(−.02)	(−2.05)	(.95)	(.25)	(2.28)	(1.28)	(−.13)	(1.95)
C. January 1983–December 1999											
CAPM alpha	−8.01	−5.33	−1.76	−1.01	.20	1.55	1.74	.70	1.81	3.38	11.39
	(−2.76)	(−2.49)	(−1.08)	(−.77)	(.17)	(1.46)	(1.54)	(.67)	(1.47)	(1.98)	(3.36)
Fama-French alpha	−5.23	−5.08	−2.69	−1.80	−.82	.37	.89	.76	1.25	5.51	10.74
	(−2.23)	(−2.46)	(−1.67)	(−1.41)	(−.72)	(.38)	(.89)	(.72)	(1.05)	(3.51)	(3.53)
Four-factor alpha	−4.43	−3.72	−1.94	−1.52	−.63	.53	.70	.47	.84	5.06	9.49
	(−1.88)	(−1.85)	(−1.21)	(−1.17)	(−.54)	(.54)	(.69)	(.44)	(.70)	(3.20)	(3.12)

NOTE.—See the note to table 3. The table reports the decile portfolios' postranking alphas, in percentages per year. The alphas are estimated as intercepts from the regressions of excess portfolio postranking returns on excess market returns (CAPM alpha), on the Fama-French factor returns (Fama-French alpha), and on the Fama-French and momentum factor returns (four-factor alphas). The t-statistics are in parentheses.

- Table 4 (Pástor and Stambaugh, 2003).
- The models are: CAPM, FF3, FF3+MOM
- *"All three alphas of the 10–1 spread are significantly positive"*.
- *"when the decile portfolios are equally weighted rather than value-weighted [...] results are even slightly stronger"*.

↪ *"The premium for this risk is positive, in that stocks with higher sensitivity to aggregate liquidity shocks offer higher expected returns."*

Post Pástor and Stambaugh (2003)

- Nagel (2012): how much have exp. returns from providing liquidity risen when mkt turmoil?
  - Proxying for returns from liquidity provision by reversal strategies, he disentangles the adverse selection from the inventory-absorption capacity effects using VIX: higher volatility tightens funding constraints of market makers.

  ↪ *"The fact that expected returns from liquidity provision are strongly related to the VIX index does not necessarily imply that the VIX index itself is the state variable [...] More likely, the VIX proxies for the underlying state variables that drive the willingness of market makers to provide liquidity and the public's demand for liquidity."* (Nagel, 2012).
- Pástor and Stambaugh (2019): 20 years after.
  - In-sample (1968–1999) vs. Out-of-sample (2000–2015) better performance: post-sample crisis produced wide fluctuations in liquidity, allowing more precise estimation of liquidity betas.
  - They exclude days with zero trading volume in the estimation.
  - *"Zeroing out the intercept could result in biased regression estimates."*
  - *"We do not use the firm-level estimates for any purpose other than to construct a market-wide measure of liquidity."*

Sorting on (Idiosyncratic) Volatility (1)

- Ang et al. (2006)'s hypothesis:
  - *"If the volatility of the market return is a systematic risk factor, the arbitrage pricing theory [...] predicts that aggregate volatility should also be priced in the cross-section of stocks. Hence, stocks with different sensitivities to innovations in aggregate volatility should have different expected returns."*
  - *" If aggregate volatility is a risk factor that is orthogonal to existing risk factors, the sensitivity of stocks to aggregate volatility times the movement in aggregate volatility will show up in the residuals of the Fama–French model [...] idiosyncratic volatility should be positively related to expected returns."*
- Findings:
  - *"Innovations in aggregate volatility carry a statistically significant negative price of risk of approximately -1% per annum."*.
  - *"We find that stocks with high idiosyncratic volatility have low average returns. There is a strongly significant difference of 1.06% per month [...] the past literature either does not examine idiosyncratic volatility at the firm level, or does not directly sort stocks into portfolios"*.

Sorting on (Idiosyncratic) Volatility (2)

- Regarding aggregate volatility: Multifactor model with FF3 and $FVIX$.
  - Measure of ex post exposure to aggregate volatility risk (monthly): mimicking portfolio that max correlates with realized innovations in volatility (ΔVIX): *"proxy aggregate volatility risk at the monthly frequency by simply cumulating daily returns"*.

  $\hookrightarrow$ Table I: the β_{FVIX} monotonically increase from 5.06 for portfolio 1 to 8.07 for portfolio 5. *"Thus, sorting stocks on past β_{FVIX} provides strong, significant spreads in ex post aggregate volatility risk sensitivities"*.
- Regarding idiosyncratic volatility:
  - Starting from FF3: $r_{i,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \epsilon_{i,t}$
    $\hookrightarrow$ Idiosyncratic risk: $\sqrt{\text{Var}(\epsilon_{i,t})}$.
  - VW Portfolios based on idiosyncratic volatility (Ivol) from daily data and *"over the 12 months of returns ending 1 month prior to the formation date. Similarly, [...] ending 2 months prior, 3 months prior, and so on [...] We then take the simple average of these 12 portfolios. Hence, each quintile portfolio changes 1/12th of its composition each month"*.(Ang et al., 2006)

Sorting on (Idiosyncratic) Volatility (3)

Rank	Mean	Std. Dev.	% Mkt Share	Size	B/M	CAPM Alpha	FF-3 Alpha
Panel A: Portfolios Sorted by Total Volatility							
1	1.06	3.71	41.7%	4.66	0.88	0.14	0.03
						[1.84]	[0.53]
2	1.15	4.48	33.7%	4.70	0.81	0.13	0.08
						[2.14]	[1.41]
3	1.22	5.63	15.5%	4.10	0.82	0.07	0.12
						[0.72]	[1.55]
4	0.99	7.15	6.7%	3.47	0.86	−0.28	−0.17
						[−1.73]	[−1.42]
5	0.09	8.30	2.4%	2.57	1.08	−1.21	−1.16
						[−5.07]	[−6.85]
5-1	−0.97					−1.35	−1.19
	[−2.86]					[−4.62]	[−5.92]
Panel B: Portfolios Sorted by Idiosyncratic Volatility Relative to FF-3							
1	1.04	3.83	53.5%	4.86	0.85	0.11	0.04
						[1.57]	[0.99]
2	1.16	4.74	27.4%	4.72	0.80	0.11	0.09
						[1.98]	[1.51]
3	1.20	5.85	11.9%	4.07	0.82	0.04	0.08
						[0.37]	[1.04]
4	0.87	7.13	5.2%	3.42	0.87	−0.38	−0.32
						[−2.32]	[−3.15]
5	−0.02	8.16	1.9%	2.52	1.10	−1.27	−1.27
						[−5.09]	[−7.68]
5-1	−1.06					−1.38	−1.31
	[−3.10]					[−4.56]	[−7.00]

- This is Table VI in Ang et al. (2006).
- *"Panel A shows that average returns increase from 1.06% per month going from quintile 1 (low total volatility stocks) to 1.22% per month for quintile 3 [...] The difference in the FF-3 alphas between portfolio 5 and portfolio 1 is 1.19% per month".*
- *"The FF-3 model is clearly unable to price these portfolios since the difference in the FF-3 alphas between portfolio 5 and portfolio 1 is 1.31% per month, with a t-statistic of 7.00."*

↪ Robust to other risk (liquidity, coskewness, momentum,..).

- Ang et al. (2009) use Fama and MacBeth (1973)'s regressions to show that the pricing hold even across countries.

Betting Against Beta (1)

- *"Many investors [...] are constrained in the leverage that they can take, and they therefore overweight risky securities [...] This behavior of tilting toward high-beta assets suggests that risky high-beta assets require lower risk-adjusted returns than low-beta assets."* (Frazzini and Pedersen, 2014).
- The starting point is a dynamic model of leverage constraints:
  - Some agents cannot leverage, so to meet their risk preference, they invest in high beta stocks.
  - High beta prices go up (exp. returns decline) while low beta stocks pay higher exp. returns.
  - Agents that can (imperfectly) leverage will go long on low beta and short on high beta.

  ↪ The Security Market Line (**HW**: what is the SML?) *"is lower because constrained agents need high unleveraged returns and are, therefore, willing to accept less compensation for higher risk"*.
- How to construct Betting Against Beta (BAB) factor factor?

$$r_{t+1}^{BAB} = \frac{1}{\beta^L}(r_{t+1}^{L} - r_f) - \frac{1}{\beta^H}(r_{t+1}^{H} - r_f)$$

↪ (ex ante) market-neutral = beta of zero: the long leg has been leveraged to a beta of one, and the short side has been de-leveraged to a beta of one.

Betting Against Beta (2)

Portfolio	P1 (low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB
Excess return	**0.91**	**0.98**	**1.00**	**1.03**	**1.05**	**1.10**	**1.05**	**1.08**	**1.06**	**0.97**	**0.70**
	(6.37)	(5.73)	(5.16)	(4.88)	(4.49)	(4.37)	(3.84)	(3.74)	(3.27)	(2.55)	(7.12)
CAPM alpha	**0.52**	**0.48**	**0.42**	**0.39**	**0.34**	**0.34**	0.22	0.21	0.10	−0.10	**0.73**
	(6.30)	(5.99)	(4.91)	(4.43)	(3.51)	(3.20)	(1.94)	(1.72)	(0.67)	(−0.48)	(7.44)
Three-factor alpha	**0.40**	**0.35**	**0.26**	**0.21**	**0.13**	0.11	−0.03	−0.06	**−0.22**	**−0.49**	**0.73**
	(6.25)	(5.95)	(4.76)	(4.13)	(2.49)	(1.94)	(−0.59)	(−1.02)	(−2.81)	(−3.68)	(7.39)
Four-factor alpha	**0.40**	**0.37**	**0.30**	**0.25**	**0.18**	**0.20**	0.09	0.11	0.01	−0.13	**0.55**
	(6.05)	(6.13)	(5.36)	(4.92)	(3.27)	(3.63)	(1.63)	(1.94)	(0.12)	(−1.01)	(5.59)
Five-factor alpha	**0.37**	**0.37**	**0.33**	**0.30**	**0.17**	**0.20**	0.11	0.14	0.02	0.00	**0.55**
	(4.54)	(4.66)	(4.50)	(4.40)	(2.44)	(2.71)	(1.40)	(1.65)	(0.21)	(−0.01)	(4.09)
Beta (ex ante)	0.64	0.79	0.88	0.97	1.05	1.12	1.21	1.31	1.44	1.70	0.00
Beta (realized)	0.67	0.87	1.00	1.10	1.22	1.32	1.42	1.51	1.66	1.85	−0.06
Volatility	15.70	18.70	21.11	23.10	25.56	27.58	29.81	31.58	35.52	41.68	10.75
Sharpe ratio	0.70	0.63	0.57	0.54	0.49	0.48	0.42	0.41	0.36	0.28	0.78

- Table 3 from Frazzini and Pedersen (2014). BAB factor delivers high alphas wrt the benchmark models: 1) against FF3: 0.73% (per month), 2) against FF3+MOM: 0.55%, 3) against FF3+MOM+LIQ: 0.55%.

  "While the alpha of the long-short portfolio is consistent across regressions, the choice of risk adjustment influences the relative alpha contribution."(Frazzini and Pedersen, 2014).

Intermediary Asset Pricing (1)

- *"Empirical asset pricing literature centers on measuring the marginal value of wealth of a representative investor, typically the average household. [...] This paper shifts attention from measuring the SDF of the average household to measuring a "financial intermediary SDF.""* (Adrian et al., 2014).
- Marginal value of wealth of intermediaries measured in leverage of security broker-dealers.
  $\hookrightarrow$ *"when funding conditions tighten and intermediaries are forced to deleverage, their marginal value of wealth should be high"*.
- Theoretical motivation: limits to arbitrage + intermediary.
  - Brunnermeier and Pedersen (2009): leverage is a proxy for funding conditions.
  - *"When funding constraints tighten, intermediaries are forced to deleverage [...] leverage directly measures such constraints and hence measures the marginal value of wealth"*.
  - Assets that covary strongly with intermediary funding conditions are thus risky.

  $\hookrightarrow$ The balance sheet capacity of intermediaries directly impacts asset price dynamics.

Intermediary Asset Pricing (2)

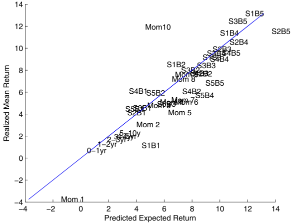


Figure 1. Realized versus predicted mean returns: leverage factor. We plot the realized mean excess returns of 35 equity portfolios (25 size- and book-to-market-sorted portfolios and 10 momentum-sorted portfolios) and six Treasury bond portfolios (sorted by maturity) against the mean excess returns predicted by our single-factor financial intermediary leverage model, estimated without an intercept ($E[R^e] = \beta_{lev}\lambda_{lev}$). The sample period is 1968Q1 to 2009Q4. Data are quarterly, but returns are expressed in percent per year.

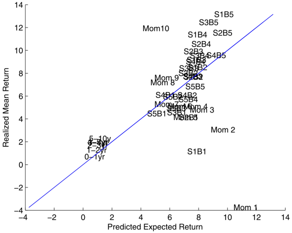


Figure 4. Realized versus predicted mean returns: Fama-French factors. We plot the realized mean excess returns of 35 equity portfolios (25 size- and book-to-market-sorted portfolios and 10 momentum-sorted portfolios) and 6 Treasury bond portfolios (sorted by maturity) against the mean excess returns predicted by the Fama-French three-factor benchmark (Mkt, SMB, HML). The sample period is 1968Q1 to 2009Q4. Data are quarterly, but returns are expressed in percent per year.

- Leverage factor: (seasonally adjusted) log changes in the broker-dealer leverage, that is the (quartely) ratio between (Total Financial Assets) an (Total Financial Assets-Total Liabilities), of security broker-dealers.
- Realized vs. predicted avg. returns in Figure 1 (leverage) and 4 (FF3) from Adrian et al. (2014): leverage factor's pricing performance in a cross-section that spans 35 common equity portfolios sorted on size, book-to-market, and momentum, and six Treasury bond.

All That Glitters is Not Gold (1)

- *"Reviewing the literature, one gets the uneasy feeling that it seems a bit too easy to explain the size and B/M effects, a concern reinforced by the fact that many [...] models have little in common economically with each other."* (Lewellen et al., 2010)
- The problem: success is linked to the high cross-sectional R^2 (or low pricing errors) when explaining avg. returns on FF 25 size-B/M portfolios.

↪ These portfolios are well known to have a strong factor structure:
  - Any factor that is (weakly) correlated with SMB or HML but not with the FF3 residuals of the size-B/M portfolios would result as "pricing".
  - *"If we do find factors that explain little of the cross-sectional variation in true expected returns, we are still reasonably likely to estimate a high cross-sectional R^2 in sample."*
    ↪ Sampling distribution of the adjusted R^2.

All That Glitters is Not Gold (2)

- Let us consider the factor model: $R_t = BF_t + e_t$.
- Economic content? The K factors can be thought of as a true pricing model.
- Hypothesis: to test a proposed model P (of J factors). We will say that P perfectly explains the cross section of expected returns if: $\mu_R = \mathbb{E}[R_t] = C\gamma$ for some RP γ and betas C.
- Testing the pricing? XS regression on the betas: $\mu_R = z\iota + C\lambda + \alpha$.
  HW: which 3 restrictions?
- We have the following observations:
  1. OBS.1. Suppose F and P have the same number of factors and their covariance is nonsingular. Then P perfectly explains the cross section of expected returns if $\text{cov}(e_t, P_t) = 0$.
     $\hookrightarrow$ many macro factors are correlated with returns primarily through FF3.
     OBS.3. When P has $J \leq K$ factors, then the XS R^2 should be J/K.
  2. OBS.2. Suppose $\text{Var}(e)$ is a diagonal matrix. Then any set of K assets perfectly explains the cross section of expected returns so long as the K assets are not asked to price themselves.
  3. OBS.4. The problems are exacerbated by sampling issues: under $\text{Var}(e)$, it can be easy to find a high sample XS R^2 even when in population is small or zero.

All That Glitters is Not Gold (3)

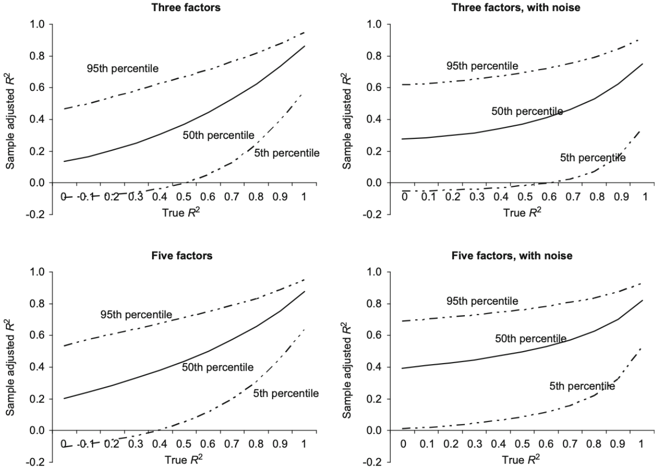


Fig. 2. The figure shows the sample distribution of the cross-sectional adjusted R^2 (average returns regressed on estimated factor loadings) as a function of the true R^2 for artificial asset-pricing models with one to five factors, using Fama and French's 25 size-*B*/*M* portfolios as test assets (quarterly returns, 1963–2004). In the left-hand panels, the factors are constructed as combinations of the 25 size-*B*/*M* portfolios (the weights are randomly drawn, as described in the text, to produce the true R^2 reported on the *x*-axis). In the right-hand panels, noise is added to the factors equal to three times their variance, to simulate factors that are not perfectly spanned by returns. The plots are based on 40,000 bootstrap simulations (ten sets of random factors; 4,000 simulations with each).

- Figure 2 from Lewellen et al. (2010).
- Factors are constructed as combinations of the 25 size-B/M portfolios (random weights): with or with/out noise.
- *"A sample adjusted R^2 must be quite high to be statistically significant, especially for models with several factors. [...] Thus, even if we could find factors that have no true explanatory power, [...] it would still not be too unusual to find fairly high R^2 in sample."*

↪ especially with especially for models with several (noisy) factors!

All That Glitters is Not Gold (4)

- What to do? Few suggestions for improving empirical tests:
  1. *"Expand the set of test portfolios beyond size-B/M portfolios"*
     ↪ use additional portfolios that do not correlate as strongly with SMB and HML.
  2. *"Take the magnitude of the cross-sectional slopes seriously"*
     ↪ the literature "does not consider whether the estimated slopes and zero-beta rates are reasonable". Ex.: zero-beta should equal the risk-free rate.
  3. *"Report the GLS cross-sectional R^2".*
  4. *"If a proposed factor is a traded portfolio, include it as one of the test assets on the left-hand side of the cross-sectional regression"*
     ↪ to incorporate pricing restriction into the XS regression by asking the factor to price itself.
  5. *"Report confidence intervals for the XS R^2*: Kan et al. (2013).
  6. *"Report confidence intervals for the weighted sum of squared pricing errors"*, ↪ confidence intervals reveals when a test has low power.

All That Publishes is Not Gold

- 97 predictors (characteristics) shown to predict XS returns in 79 peer-reviewed top journals.
- No study compares in-sample returns, post-sample returns, and post-publication returns.

↪ McLean and Pontiff (2016): *"our goal is to better understand what happens to return predictability outside a study's sample period"*.

  - They study the performance of these predictors during two out-of-sample periods: a) Once the paper is publicly available, but before publication, b) Following publication.

$$R_{i,t} = \alpha_0 + \alpha_1 \text{Post-sample-dummy}_{i,t} + \alpha_2 \text{Post-pub-dummy}_{i,t}$$

  where $R_{i,t}$ is the monthly return for predictor i in month t.

  ↪ Both α_1, α_2 negative and significant.

- *"The average predictor's long-short return shrinks 58% post-publication. Combining this finding with an estimated statistical bias of 26% implies a lower bound on the publication effect of about 32%. We can reject the hypothesis that return predictability disappears entirely, and we can also reject the hypothesis that post-publication return predictability does not change. This post-publication decline is robust to a general time trend, to time indicators used by other authors, and to time fixed effects."* (McLean and Pontiff, 2016)

...and The Factor Zoo

- Harvey et al. (2016): *"Hundreds of papers and factors attempt to explain the cross-section of expected returns. Given this extensive data mining, it does not make sense to use the usual criteria for establishing significance"*.

↪ *"We begin with 313 papers published in a selection of journals that study the cross/sectional return patterns"*.

- Risk dimensions: a) financial, b) macro, c) microstructure, d) behavioural, e) accounting, e) other (e.g., past returns, intangibles, political risk).
- *"There are two ways to deal with the bias introduced by multiple testing: out-of-sample validation and using a statistical framework that allows for multiple testing"*.

↪ higher cutoffs given the factor production: *"a new factor needs to clear a much higher hurdgle, with a t-statistic greater than 3.0"* (vs. 1.96).

- Chen and Zimmermann (2022) have done a great job in making the zoo available: click here

Thanks for your attention! See you next Monday!

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