Risk factors out-of-sample

Empirical Asset Pricing

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Risk factors out-of-sample

- There is great debate about the number and identification of reliable risk factors and cross-sectional return predictors (Harvey et al., 2016, Harvey, 2017, McLean and Pontiff, 2016, Linnainmaa and Roberts, 2018, Engelberg et al., 2018, Calluzzo et al., 2019, Chen and Zimmermann, 2020, Chen, 2021a, Chen and Zimmermann, 2021, Jensen et al., 2021, Harvey and Liu, 2021)

The opposing sides of the debate

Dark side: Factors are false

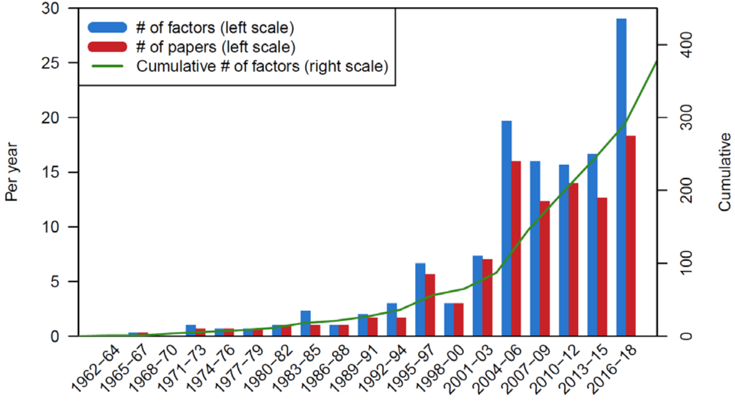
1. Data-mining
2. p-hacking
3. Chance result
4. Replication crisis

Bright side: Factors are real

1. Economically motivated
2. Robustness checks
3. Mispricing
4. Factors replicate

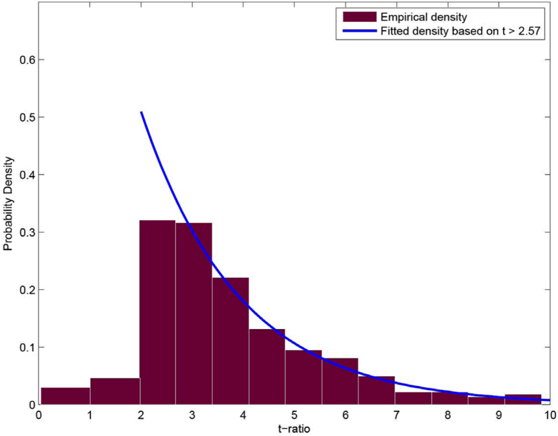
Factor production is rampant

- Harvey and Liu (2019) provide a census of the proverbial factor zoo (Cochrane, 2011, Harvey et al., 2016) Google sheet with factors
- The below figure details the factor production from 1963–2018 and clearly indicates a strong increase (382 factors in top journals alone)



* Journals published through December 2018. Data collection in January 2019.

- Harvey (2017) argues that the distribution of reported t-statistics is indicative of a publication bias and p-hacking
- In particular, note that t-statistics in the range of 2.0 to 2.57 is almost the same as the number reporting in the range of 2.57 to 3.14. Also, notice that very few papers with negative results (t-statistic less than 2.00) are published



McLean and Pontiff (2016)

McLean and Pontiff (2016)

- McLean and Pontiff (2016) ask the following question: Does cross-sectional return predictability typically persists post-publication?
- To investigate this, they consider 97 cross-sectional return predictors (or risk factors) over three distinct periods
  1. The original study's sample period
  2. The out-of-sample period (post-sample, pre-publication)
  3. The post-publication period
- Examining the behavior of returns over these three periods, we can distinguish between three possible explanations
  1. Statistical bias $\Rightarrow$ Predictability should disappear out-of-sample
  2. Rational risk $\Rightarrow$ Predictability should be the same in-sample, out-of-sample, and post-publication
  3. Mispricing $\Rightarrow$ If arbitrage is costless, then it should disappear completely. If arbitrage is costly, then the effect should at least decay post-publication

Summary of main findings

- The main findings in McLean and Pontiff (2016) can be summarized as follows

  1. The average predictor's long-short return declines by 26% out-of-sample
     - One can view this as an upper bound on the effect of statistical biases!
  2. The average predictor's long-short return shrinks 58% post-publication
     - Together with the 26% out-of-sample decline, this implies a lower bound on the publication effect of about 32%
     - Rejection of the hypothesis that return predictability disappears completely and that predictability post-publication is unchanged
  3. The decay in portfolio returns is larger for predictor portfolios with higher in-sample returns and t-statistics
  4. Post-publication returns are lower for predictors that are less costly to arbitrage, i.e., portfolios concentrated in liquid and low idiosyncratic risk stocks
  5. Publication affects the correlation between predictor portfolio returns. (Yet-to-be) published predictors are highly correlated with (yet-to-be) published

$\Rightarrow$ The empirical evidence suggests that investors learn about mispricing from academic publications

Summary statisics

- The below table provides an overview of the characteristics of the data. Note that only 85 of the 97 predictors have a t-statistic above 1.5

Number of predictor portfolios	97
Predictors portfolios with t-statistic > 1.5	85 (88%)
Mean publication year	2000
Median publication year	2001
Predictors from finance journals	68 (70%)
Predictors from accounting journals	27 (28%)
Predictors from economics journals	2 (2%)
Mean portfolio return in-sample	0.582
Standard deviation of mean in-sample portfolio return	0.395
Mean observations in-sample	323
Mean portfolio return out-of sample	0.402
Standard deviation of mean out-of-sample portfolio return	0.651
Mean observations out-of-sample	56
Mean portfolio return post-publication	0.264
Standard deviation of mean post-publication portfolio return	0.516
Mean observations post-publication	156

Cross-sectional predictors

- In their Internet Appendix, they provide a full list of predictors and their classification into four broad categories (plus definitions)

Event	Market	Valuation	Fundamental
Change in Asset Turnover	52-Week High	Advertising/MV	Accruals
Change in Profit Margin	Age-Momentum	Analyst Value	Age
Change in Recommendation	Amihud's Measure	Book-to-Market	Asset Growth
Chg. Forecast + Accrual	Beta	Cash Flow/MV	Asset Turnover
Debt Issuance	Bid/Ask Spread	Dividends	Cash Flow Variance
Dividend Initiation	Coskewness	Earnings-to-Price	Earnings Consistency
Dividend Omission	Idiosyncratic Risk	Enterprise Component of B/P	Forecast Dispersion
Dividends	Industry Momentum	Enterprise Multiple	G Index
Down Forecast	Lagged Momentum	Leverage Component of B/P	Gross Profitability
Exchange Switch	Long-term Reversal	Marketing/MV	G-Score
Growth in Inventory	Max	Org. Capital	G-Score 2
Growth in LTNOA	Momentum	R&D/MV	Herfindahl
IPO	Momentum and Long-term Reversal	Sales/Price	Investment
IPO + Age	Momentum-Ratings		Leverage
IPO no R&D	Momentum-Reversal		M/B and Accruals
Mergers	Price		NOA
Post Earnings Drift	Seasonality		Operating Leverage
R&D Increases	Short Interest		O-Score
Ratings Downgrades	Short-term Reversal		Pension Funding
Repurchases	Size		Percent Operating Accrual
Revenue Surprises	Volume		Percent Total Accrual
SEOs	Volume Trend		Profit Margin
Share Issuance 1-Year	Volume Variance		Profitability
Share Issuance 5-Year	Volume-Momentum		ROE
Spinoffs	Volume/MV		Sales Growth
Sustainable Growth			Tax
Total External Finance			Z-Score
Up Forecast			
ΔCapex - ΔIndustry CAPEX			
ΔNoncurrent Op. Assets			
ΔSales - ΔInventory			
ΔSales - ΔSG&A			
ΔWork. Capital			

Returns post-sample and post-publication

- The main panel regression of the paper is specified as follows (where α_i captures predictor fixed effects)

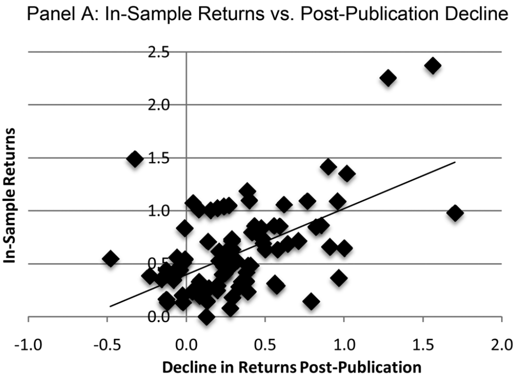
$$R_{it} = \alpha_i + \beta_1 \text{Post sample dummy}_{it} + \beta_2 \text{Post publication dummy}_{it} + e_{it} \tag{1}$$

Variables	(1)	(2)	(3)	(4)
Post-Sample (S)	−0.150***	−0.180**	0.157	0.067
	(0.077)	(0.085)	(0.103)	(0.112)
Post-Publication (P)	−0.337***	−0.387***	−0.002	−0.120
	(0.090)	(0.097)	(0.078)	(0.114)
S × Mean			−0.532***	
			(0.221)	
P × Mean			−0.548***	
			(0.178)	
S × *t*-statistic				−0.061***
				(0.023)
P × *t*-statistic				−0.063***
				(0.018)
Predictor FE?	Yes	Yes	Yes	Yes
Observations	51,851	45,465	51,851	51,944
Predictors (N)	97	85	97	97
Null : S = P	0.024	0.021		
Null: P = −1 × (mean)	0.000	0.000		
Null: S = −1 × (mean)	0.000	0.000		

- We have reductions in returns of $15/58.2 = 26\%$ and $33.7/58.2 = 58\%$, respectively, relative to the average in-sample return of 58.2bps

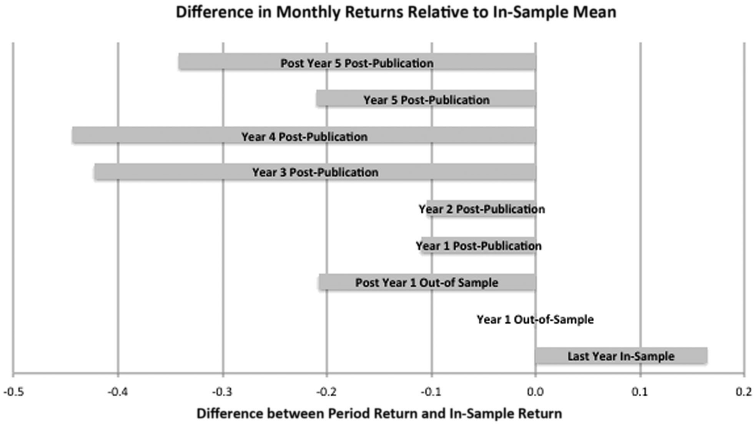
In-sample returns and post-publication decline

- Higher in-sample returns are correlated with larger reductions in post-publication returns (similar for t-statistics)



Returns around sample-end and publication dates

- We then examine changes in predictability by considering a set of partitions of the sample in event time at higher granularity



- Are the results due to time trends, persistencies, or lower costs of *corrective* trading instead of academic research?
- The results are not supportive of this hypothesis

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Time	−0.069***		−0.069***			
	(0.011)		(0.026)			
Post-1993		−0.120	0.303***			
		(0.074)	(0.118)			
Post-Sample			−0.190**	−0.179**	−0.132*	−0.128
			(0.081)	(0.080)	(0.076)	(0.078)
Post-Publication			−0.362***	−0.310**	−0.295***	−0.258***
			(0.124)	(0.122)	(0.089)	(0.093)
1-Month Return					0.114***	
					(0.015)	
12-Month Return						0.020***
						(0.004)
Observations	51,851	51,851	51,851	51,851	51,754	50,687
Char. FE?	Yes	Yes	Yes	Yes	Yes	Yes
Time FE?	No	No	No	Yes	No	No

Returns across predictor types

- To test for differences among predictor groups, we can run the following regression model

$$R_{it} = \alpha_i + \beta_1 \text{Post publication dummy}_{it} + \beta_2 \text{Predictor type dummy}_i + \beta_3 \text{Post publication dummy}_{it} \times \text{Predictor type dummy}_i + e_{it} \quad (2)$$

Variable	(1)	(2)	(3)	(4)
Post-Publication (P)	−0.208***	−0.316***	−0.310***	−0.301***
	(0.059)	(0.097)	(0.080)	(0.089)
Market	0.304***			
	(0.079)			
P × Market	−0.244			
	(0.169)			
Event		−0.098**		
		(0.046)		
P × Event		0.105		
		(0.091)		
Valuation			−0.056	
			(0.063)	
P × Valuation			0.186	
			(0.131)	
Fundamental				−0.201***
				(0.045)
P × Fundamental				0.025
				(0.089)
Constant	0.482***	0.606***	0.585***	0.630***
	(0.036)	(0.052)	(0.000)	(0.053)
Observations	51,851	51,851	51,851	51,851
Predictors	97	97	97	97
Type + (P × Type)	0.060	0.007	0.121	−0.176
p-value	0.210	0.922	0.256	0.012

Costly arbitrage

- The results so far are consistent with the idea that publication attracts arbitrageurs, which leads to lower returns post-publication

- Costly arbitrage can prevent mispricing from being fully eroded, which suggests that predictor portfolios concentrated in stocks that are costlier to arbitage (e.g., smaller stocks, illiquid stocks, and high idiosyncratic risk stocks) should decline less post-publication

- McLean and Pontiff (2016) consider three transaction costs variables (size, bid-ask spreads, dollar volume) and two holding cost variables (idiosyncratic risk, dividend-payer dummy) and run the following regression model

$$\begin{aligned} R_{it} = \alpha_i &+ \beta_1 \text{Post publication dummy}_{it} + \beta_2 \text{Arbitrage cost}_i \\ &+ \beta_3 \text{Post publication dummy}_{it} \times \text{Arbitrage cost}_i + e_{it} \end{aligned} \tag{3}$$

Costly arbitrage results

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Post-Pub. (P)	−0.190	−0.139	0.215	−0.242	−0.321	−0.264**
	(0.274)	(0.235)	(0.230)	(0.273)	(0.211)	(0.078)
P × Size	−0.138					
	(0.459)					
Size	−1.064**					
	(0.236)					
P × Spreads		−0.301				
		(0.603)				
Spreads		1.228**				
		(0.252)				
P × Dol.Vol.			−1.059*			
			(0.500)			
Dol. Vol.			0.215			
			(0.308)			
P × Idio. Risk				−0.047		
				(0.554)		
Idio. Risk				2.064***		
				(0.330)		
P × Div.					−0.321	
					(0.211)	
Div.					−0.526***	
					(0.145)	
P × Index						−0.009
						(0.019)
Index						−0.056***
						(0.011)
Constant	1.145***	0.146*	0.476***	−0.469***	0.855***	0.565***
	(0.130)	(0.174)	(0.144)	(0.171)	(0.097)	(0.000)
Observations	51,851	51,851	51,851	51,851	51,851	51,851
CA + (P × CA)	−1.202	0.927	−0.844	2.017	−0.847	−0.065
p-value	0.003	0.096	0.000	0.000	0.144	0.000

Post-sample and -publication trading activity dynamics

- If academic publication provides market participants with information, then informed trading activity should affect indicators of trading beyond prices
- Below, we investigate whether variance, trading volume, dollar trading volume, and short interest increase in predictor portfolios post-publication
- Note that a significant post-sample coefficient is indicative of the informational content being out prior to publication (e.g., working papers and conferences)

Variables	Variance	Trading volume	Dollar volume	Short-long short interest
Post-Sample (S)	−0.054***	0.092***	0.066***	0.166***
	(0.007)	(0.001)	(0.007)	(0.014)
Post-Publication (P)	−0.065***	0.187***	0.097***	0.315***
	(0.008	(0.013)	(0.007)	(0.013)
Observations	52,632	52,632	52,632	41,026
Time FE?	Yes	Yes	Yes	No
Predictor FE?	Yes	Yes	Yes	Yes
Null: S = P	0.156	0.000	0.000	0.000

Correlation structure and publication

- If predictor returns reflect mispring, and if mispricing has a common source, then we should expect that
  1. In-sample returns are significantly related to other in-sample portfolios
  2. Once a predictor is published (and attracts arbitrageurs), its return should correlate (less) more with the returns of other (pre-) post-publication predictors
- We examine this by regressing predictor portfolio returns on the returns of an
  1. equal-weighted index of all other portfolios that are pre-publication
  2. equal-weighted index of all of the other portfolios that are post-publication
  3. A post-publication dummy and interactions with the indices

Variables	Coefficients
In-Sample Index Returns	0.748***
	(0.027)
Post-Publication Index Return	−0.008
	(0.004)
P × In-Sample Index Returns	−0.674***
	(0.033)
P × Post-Publication Index Return	0.652***
	(0.045)
Publication (P)	−0.081
	(0.042)
Constant	0.144***
	(0.019)
Observations	42,975
Predictors	97

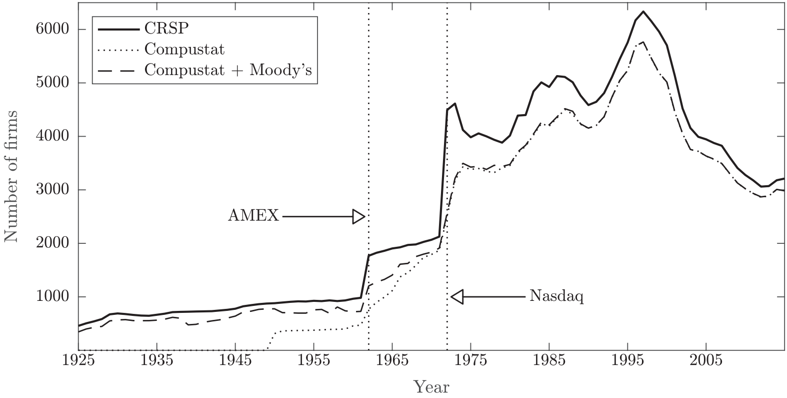
Linnainmaa and Roberts (2018)

Linnainmaa and Roberts (2018)

- Linnainmaa and Roberts (2018) ask the following question: Does accounting-based anomalies persist out-of-sample (both pre- and post-sample)?
- To examine this, they consider a broad selection of 36 accounting-based anomalies over three distinct periods
  1. "In-sample" denotes the sample frame used in the original discovery of an anomaly
  2. "Pre-sample" denotes the sample frame occurring prior to the in-sample period
  3. "Post-sample" denotes the sample frame occurring after the in-sample period
- Similar to McLean and Pontiff (2016), they distinguish between three possible explanations
  1. Unmodeled risk $\Rightarrow$ Stocks risk are multidimensional and models are misspecified
  2. Mispricing $\Rightarrow$ Investor irrationality and limits to arbitrage cause anomaly returns
  3. Data-snooping $\Rightarrow$ Anomalies are artifacts of chance error
- **Main conclusion:** Most anomaly returns are decidedly an in-sample phenomenon consistent with data-snooping (i.e., most risk factors are false)

Number of firms available

- One of the main contribution of Linnainmaa and Roberts (2018) is to back-fill accounting information using Moody's Industrial and Railroad manuals to obtain out-of-sample data points back in time
- See also Baltussen et al. (2021) for a paper constructing a pre-CRSP dataset



Case study: Fama-French five factors

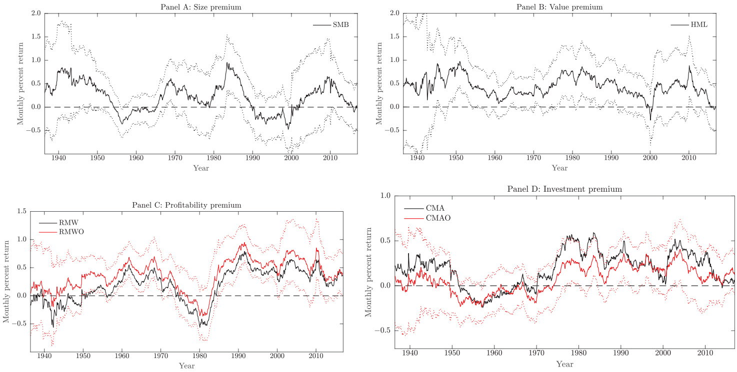
- To illustrate their approach, consider the case of the Fama and French (2015) five-factor model using pre-1963 accounting data

Panel A: Monthly percent returns

	Pre-1963 sample			
Portfolio	1926:7 –1938:6	1938:7 –1963:6	1926:7 –1963:6	1963:7 –2016:12
	Portfolios sorted by size and book-to-market			
Small Growth	0.73	1.17	1.03	0.88
Neutral	1.04	1.32	1.23	1.29
Value	1.41	1.62	1.55	1.40
Big Growth	0.80	0.99	0.93	0.88
Neutral	0.73	1.16	1.02	0.96
Value	0.88	1.51	1.31	1.13
Size factor	0.26	0.15	0.18	0.20
	(0.62)	(1.05)	(1.11)	(1.54)
Value factor	0.38	0.48	0.45	0.38
	(0.66)	(2.87)	(2.06)	(3.40)
	Portfolios sorted by size and profitability			
Small Weak	0.88	1.32	1.18	0.96
Neutral	0.78	1.38	1.19	1.24
Robust	0.75	1.37	1.17	1.31
Big Weak	0.81	1.09	1.00	0.83
Neutral	0.76	1.10	0.99	0.90
Robust	0.68	1.23	1.05	1.03
Profitability factor	−0.13	0.09	0.02	0.28
	(−0.31)	(0.64)	(0.14)	(3.09)
	Portfolios sorted by size and investment			
Small Aggressive	0.84	1.23	1.10	0.98
Neutral	1.58	1.36	1.43	1.34
Conservative	1.06	1.36	1.27	1.33
Big Aggressive	0.69	1.11	0.97	0.90
Neutral	1.14	1.12	1.13	0.94
Conservative	0.86	1.04	0.98	1.08
Investment factor	0.19	0.03	0.09	0.26
	(0.79)	(0.32)	(0.80)	(3.28)

The dynamics of FF5 factor premiums

- Consider the ten-year rolling window average returns to the Fama and French (2015) factors
- See also Fama and French (2021) for a discussion of the recent performance of the value premium



Risk factors under consideration

- The 36 accounting-based anomalies under consideration, and their groupings, are specified below and information about the construction can be found in the paper appendix

Category	No.	Anomaly	Original study	Original sample
Profitability	1	Gross profitability	Novy-Marx (2013)	1963–2010
	2	**Operating profitability***	Fama and French (2015)	1963–2013
	3	Return on assets*	Haugen and Baker (1996)	1979–1993
	4	Return on equity*	Haugen and Baker (1996)	1979–1993
	5	Profit margin	Soliman (2008)	1984–2002
	6	Change in asset turnover	Soliman (2008)	1984–2002
Earnings quality	7	Accruals*	Sloan (1996)	1962–1991
	8	Net operating assets	Hirshleifer, Hou, Teoh, and Zhang (2004)	1964–2002
	9	Net working capital changes	Soliman (2008)	1984–2002
Valuation	10	**Book-to-market**	Fama and French (1992)	1963–1990
	11	Cash flow / price	Lakonishok, Shleifer, and Vishny (1994)	1968–1990
	12	Earnings / price	Basu (1977)	1957–1971
	13	Enterprise multiple*	Loughran and Wellman (2011)	1963–2009
	14	Sales / price	Barbee, Mukherji, and Raines (1996)	1979–1991
Investment and growth	15	**Asset growth**	Cooper, Gulen, and Schill (2008)	1968–2003
	16	Growth in inventory	Thomas and Zhang (2002)	1970–1997
	17	Sales growth	Lakonishok, Shleifer, and Vishny (1994)	1968–1990
	18	Sustainable growth	Lockwood and Prombutr (2010)	1964–2007
	19	Adjusted CAPX growth*	Abarbanell and Bushee (1998)	1974–1993
	20	Growth in sales − inventory	Abarbanell and Bushee (1998)	1974–1993
	21	Investment growth rate*	Xing (2008)	1964–2003
	22	Abnormal capital investment*	Titman, Wei, and Xie (2004)	1973–1996
	23	Investment to capital*	Xing (2008)	1964–2003
	24	Investment-to-assets	Lyandres, Sun, and Zhang (2008)	1970–2005
Financing	25	Debt issuance*	Spiess and Affleck-Graves (1999)	1975–1994
	26	Leverage	Bhandari (1988)	1948–1979
	27	One-year share issuance	Pontiff and Woodgate (2008)	1970–2003
	28	Five-year share issuance	Daniel and Titman (2006)	1968–2003
	29	Total external financing*	Bradshaw, Richardson, and Sloan (2006)	1971–2000
Distress	30	O-score	Dichev (1998)	1981–1995
	31	z-score*	Dichev (1998)	1981–1995
	32	Distress risk	Campbell, Hilscher, and Szilagyi (2008)	1963–2003
Other	33	Industry concentration	Hou and Robinson (2006)	1951–2001
Composite anomalies	34	Piotroski's F-score	Piotroski (2000)	1976–1996
	35	M/B and accruals*	Bartov and Kim (2004)	1981–2000
	36	QMJ: Profitability	Asness, Frazzini, and Pedersen (2013)	1956–2012

Returns in pre-, in-, and post-sample periods

- The main result of Linnainmaa and Roberts (2018) is that anomaly returns are a decidedly in-sample phenomenon, which is clearly evident in their Table 6

				Differences		
Measure	Pre-sample	In-sample	Post-sample	Pre − In	Post − In	Post − Pre
Panel A: Full pre-1963 sample						
			Average returns			
Average	0.08	0.29	0.09	−0.21	−0.20	0.00
return	(2.21)	(7.01)	(1.72)	(−3.78)	(−3.69)	(0.03)
Sharpe	0.15	0.54	0.13	−0.39	−0.42	−0.03
ratio	(3.38)	(7.57)	(1.52)	(−4.71)	(−4.14)	(−0.30)
			CAPM			
Alpha	0.15	0.34	0.17	−0.20	−0.18	0.02
	(4.80)	(9.75)	(3.50)	(−4.27)	(−3.44)	(0.38)
Information	0.22	0.66	0.27	−0.43	−0.40	0.04
ratio	(5.08)	(9.72)	(2.99)	(−5.43)	(−3.83)	(0.43)
			Three-factor model			
Alpha	0.17	0.27	0.12	−0.10	−0.15	−0.05
	(6.42)	(10.12)	(3.19)	(−2.57)	(−3.44)	(−1.10)
Information	0.28	0.60	0.25	−0.32	−0.35	−0.03
ratio	(6.35)	(9.91)	(2.86)	(−4.26)	(−3.46)	(−0.32)

Effect of state date on returns

- To investigate the sensitivity to the in-sample period, Linnainmaa and Roberts (2018) run a panel regression of the form

$$\text{anomaly}_{it} = \beta_0 + \beta_1 \text{Pre-sample}_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

where μ_i is an anomaly fixed effect and Pre-sample_{it} is an indicator equal to one if the anomaly-month observation falls in the time period before the start date of the anomaly's in-sample start date

	Average return		CAPM alpha		FF3 alpha		
Start year	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_0$	$\hat{\beta}_1$	No. of obs.
1963	0.30	−0.15	0.36	−0.18	0.27	−0.14	14,793
	(6.77)	(−2.16)	(10.07)	(−2.97)	(10.35)	(−3.18)	
1964	0.30	−0.15	0.36	−0.19	0.28	−0.13	14,385
	(6.77)	(−1.93)	(10.06)	(−2.86)	(10.40)	(−2.68)	
1965	0.30	−0.13	0.36	−0.17	0.28	−0.11	13,977
	(6.78)	(−1.58)	(10.07)	(−2.42)	(10.40)	(−2.27)	
1966	0.30	−0.13	0.37	−0.17	0.28	−0.12	13,569
	(6.84)	(−1.46)	(10.15)	(−2.26)	(10.45)	(−2.21)	
1967	0.31	−0.09	0.37	−0.13	0.29	−0.12	13,161
	(6.89)	(−0.98)	(10.21)	(−1.84)	(10.50)	(−2.25)	
1968	0.31	−0.07	0.37	−0.13	0.29	−0.13	12,753
	(6.90)	(−0.80)	(10.20)	(−2.07)	(10.45)	(−2.31)	
1969	0.31	−0.11	0.38	−0.17	0.29	−0.18	12,345
	(6.77)	(−1.21)	(10.09)	(−2.53)	(10.44)	(−3.04)	
1970	0.30	−0.22	0.37	−0.24	0.29	−0.25	11,937
	(6.53)	(−2.68)	(9.91)	(−3.37)	(10.22)	(−4.12)	
1971	0.31	−0.22	0.37	−0.26	0.29	−0.28	11,532
	(6.63)	(−2.65)	(9.88)	(−3.78)	(10.02)	(−4.60)	
1972	0.32	−0.21	0.38	−0.26	0.29	−0.31	11,136
	(6.64)	(−2.18)	(9.86)	(−3.24)	(9.86)	(−4.52)	
1973	0.31	−0.24	0.38	−0.28	0.31	−0.27	10,740
	(6.38)	(−2.20)	(9.70)	(−3.31)	(10.17)	(−3.51)	

Volatility across the eras

- Linnainmaa and Roberts (2018) argue that data-snooping works through t-values, so examining volatility across the three periods may be worthwhile
- Consider the panel regression specification for squared demeaned returns

$$(\text{anomaly}_{it} - \bar{r}_{it})^2 = \beta_0 + \beta_1 \text{In-sample}_{it} + \beta_2 \text{Post-sample}_{it} + \mu_{it} + \varepsilon_{it} \quad (5)$$

- Estimating the model yields the following parameter estimates
  - $\beta_1 = -0.61$ with a t-stat of -2.88
  - $\beta_2 = 0.38$ with a t-stat of 0.79

  indicating that volatility is lower during the in-sample period, which is consistent with data-snooping contaminating the distribution of in-sample returns

Changes in correlation structure of returns

- Finally, we can investigate effects upon the correlation structure as in McLean and Pontiff (2016) by running the regression

$$\begin{aligned}\text{anomaly}_{it} &= a + b_1 \text{in-sample index}_{-i,t} + b_2 \text{post-sample index}_{-i,t} + b_3 \text{post}_{it} \\ &+ \text{post}_{it} \times \left(b_4 \text{in-sample index}_{-i,t} + b_5 \text{post-sample index}_{-i,t}\right) + e_{i,t}\end{aligned}$$

Regressor	Coefficient	t-value
Regression 1: In-sample versus post-sample anomalies		
Intercept	0.05	4.54
Main effects		
In-sample index$_{-i,t}$	0.74	33.98
Post-sample index$_{-i,t}$	0.08	7.46
Post$_{i,t}$	−0.06	−2.23
Interactions		
Post$_{i,t}$ × In-sample index$_{-i,t}$	−0.53	−13.74
Post$_{i,t}$ × Post-sample index$_{-i,t}$	0.46	11.19
Adjusted R^2		17.9%
N		15,152
Regression 2: In-sample versus pre-sample anomalies		
Intercept	0.07	4.35
Main effects		
In-sample index$_{-i,t}$	0.74	28.90
Pre-sample index$_{-i,t}$	0.07	3.42
Pre$_{i,t}$	−0.04	−2.09
Interactions		
Pre$_{i,t}$ × In-sample index$_{-i,t}$	−0.69	−22.72
Pre$_{i,t}$ × Pre-sample index$_{-i,t}$	0.48	13.68
Adjusted R^2		9.3%
N		13,650

Other perspectives in the debate

Factors are mostly false

- There is a large camp, mainly headed by Campbell R. Harvey, that claims that most factors are false and that there is a pronounced replication crisis in finance (Harvey et al., 2016, Harvey, 2017, Harvey and Liu, 2019, 2021)
  - Hou et al. (2020) re-evaluate 452 anomalies and find that mitigating for microcaps using NYSE breakpoints and value-weighted returns leads to a failure rate of 65% using a 1.96 cutoff. It increases to a failure rate of 82% using a cutoff of 2.78
  - Tian (2020) runs a data-mining experiment in which she randomly constructs hundreds of three-factor models. She finds that many outperform well known models from the literature, including those with four and five factor. This suggest that the threshold of factor model success needs to be raised
  - Chordia et al. (2020) use information from over 2 million randomly generated trading strategies (using real data and strategies that survive the publication process) to infer the statistical properties of factor strategies. They compute t-statistic threshold that control for multiple hypothesis testing at 3.8 and 3.4 for time-series and cross-sectional regressions, respectively, Failing to account for multiple hypothesis testing leads to a false rejection about 45% of the time

Factors are mostly true

- There is similarly a growing literature arguing that most factors are true and can be successfully replicated
  - Engelberg et al. (2018) find that anomaly returns are 50% higher on corporate news days and six times higher on earnings announcement days. They argue that the results point to the idea that anomaly returns are driven by biased expectations that are (partly) corrected by information arrivals
  - Jacobs and Müller (2020) extend the work of McLean and Pontiff (2016) by investigating 241 anomalies in 39 countries. Their results similar point to mispricing rather than data mining
  - Calluzzo et al. (2019) show that there is an increase in anomaly-related trading when information about the anomalies is readily available through academic publications
  - Chen and Zimmermann (2020) argue that bias-adjusted returns are only 12.3% smaller than in-sample returns, which is well within the McLean and Pontiff (2016) upper bounds and points to mispricing
  - Chen (2021a,b) provides thought experiments and alternative views on the results of Harvey et al. (2016) and argues that p-hacking cannot be as widely applied as argued and that most factors are true as a consequence
  - Jensen et al. (2021) challenge the dire view of finance research. They develop and estimate a Bayesian model of factor replication, which leads to different conclusions. They find a baseline replication rate as high as 55.6%! (plus make available a new global dataset at https://www.bryankellyacademic.org under Data)

Time-varying factor returns

- The entire debate so far, has taken an unconditional view; meaning that we do not take into account that many of the factors are related to the business cycle
- Kelly and Pruitt (2013) find that bm ratios predicts momentum, size, and industry portfolios
- Baba Yara et al. (2021) find that the value spread predicts the return value strategies across many different assets
- Haddad et al. (2020) show that common components of anomalies are predictable (OoS) using their value spread $\rightarrow$ exploitable for factor timing!
- Smith and Timmermann (2022) find "breaks" in the risk premium of many anomalies during times of economic turbulence

Factor momentum

- More recently, a couple of papers has examined factor momentum
- Avramov et al. (2017) show that sorting factors on most recent performance is highly profitable
- Ehsani and Linnainmaa (2022) show that the momentum factor can be fully explained by factor momentum (TS momentum)
- Arnott et al. (2023) show that cross-sectional factor momentum has high alphas

➜ Factors seems to have autocorrelation that you can exploit!

Open source asset pricing

- Last, I want to direct attention to a great initiative and a compelling voice in the debate about replicability in finance: https://www.openassetpricing.com
- Chen and Zimmermann (2021) provide open source code, characteristics data, and portfolio returns for about 200 (204 to be precise) factor portfolios
- This is a great source of data for re-examining cross-sectional predictors by combining their data with the CRSP database (you can do that using PERMNO)

Let us examine short term factor momentum!

- We consider the (scaled) characteristics from Chen and Zimmermann (2021) which we merge with our CRSP dataset
- Data from 1986 to 2019
- Follow the recommendations of Hou et al. (2020), i.e. NYSE-based breakpoints, VW portfolios, and consider quintile portfolios.
- Each factor is defined as long in portfolio 5 and short portfolio 1
- Some of the factors in Chen and Zimmermann (2021) are based on discrete chacteristics (such as the sin factor). We will ignore these
- We then sort our CS of factors based on most recent performance (t-1 return) into 5 EW portfolios

Short term factor momentum is highly profitable!

- The five factor portfolios generates the following average returns:

	1	2	3	4	5	5-1
Average returns	-0.36	1.53	3.07	4.09	8.53	8.89
SR	-0.04	0.33	1.07	0.89	0.85	0.47
t-stat	-0.23	1.73	5.78	5.50	6.05	3.25

➜ Factor performance is an increasing function of most recent factor performance!

Aaand over time

➜ Factor momentum has disappreared since 2010... Why?

Potential projects

Potential projects

- Investigate the returns and pricing ability pre- and post-publication to anomalies/factors
- Investigate whether there are publication effects in other asset classes (e.g., currencies or bonds)
- Combine a CRSP-based portfolio sorts or a cross-sectional asset pricing exercise with robustness checks inspired by this literature (e.g., re-examine with stricter thresholds)
- Test whether selected time-series predictors similarly display publication effects inspired by this literature
- Re-examine selected risk factors/anomalies out-of-sample and investigated whether results can be replicated and extended

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