



What Do We Know about Factor Investing?

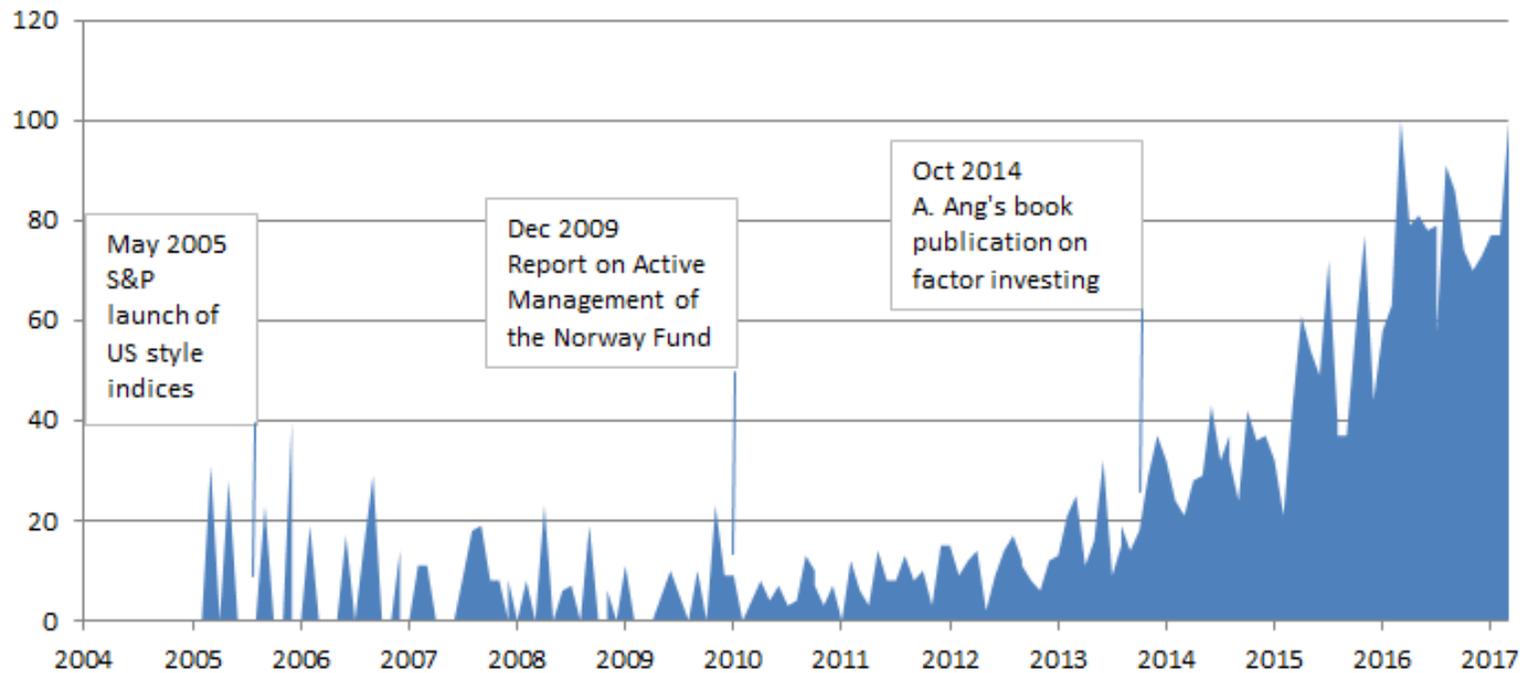
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Frontiers of Factor Investing, Lancaster University, April 2018

Factor Investing: A Lively Field

— Google Trends for « Factor Investing »



Source: Google Trends, Apr 2017

A Short History of Risk Factors...

- The first factor
 - Sharpe-Lintner-Mossin-Treynor CAPM (1964): **the market is the key risk factor** (at least for equities)
- Early additions to the market factor
 - Ross (1976) Arbitrage Pricing Theory: other risk factors exist
 - Fama and French (1992) introduce the **size and value factors**
 - Jegadeesh and Titman (1993) and Carhart (1997) add **the momentum factor**
- A bulk of new factors
 - Quality, low beta, etc.
 - Fama and French (2014) add **two quality (profitability and investment) factors**
 - **Many factors** have been proposed (Harvey et al., 2015)

... and Factor Investing

- Ang, Goetzmann and Schaefer (2009): report to the Norwegian Sovereign Wealth Fund
 - A substantial part of active returns can be explained by exposure to risk factors
 - Recommend to allocate portfolio risks among these factors
 - Started a new conversation about asset allocation
- Using risk factors for asset allocation
 - Aggregate securities by their exposure to pre-defined factors
 - Asset allocation based on “factor indices”
 - Factor-based investment: "new paradigm for long term investment" (Ang, 2014)

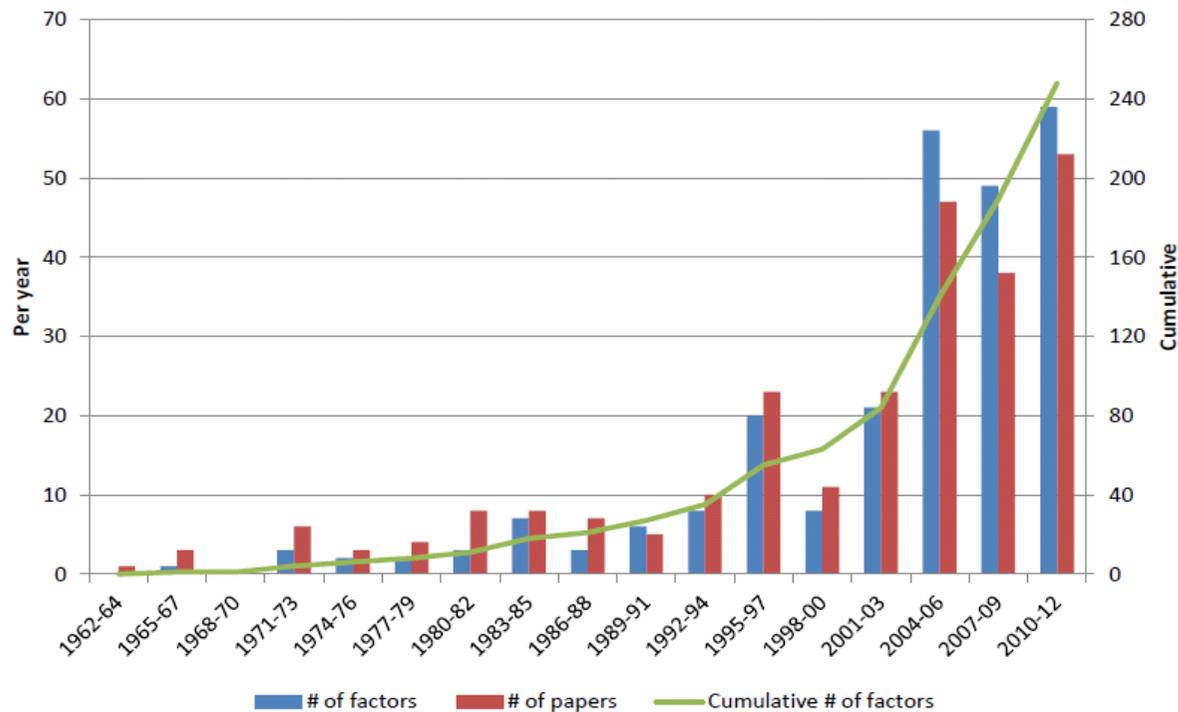
Key Questions

- Identifying Risk Factors
 - Factor proliferation and data snooping
 - Back to Basics: competing factor models
 - Risk factors or anomalies?
- Factor Investing: A New Paradigm?
 - Factor diversification
 - Factors long-only or long-short?
 - Factor mix or stock selection across multiple characteristics?
 - Factor timing: Is it worth it?
- What Next?
 - Key Takeaways
 - Further questions: factor transaction costs and crowding

Identifying Risk Factors

Factor Proliferation

- More than 300 discovered equity factors (Harvey et al., 2015)
 - Cochrane (2011) refers to a “zoo” of factors



Too Many Factors?

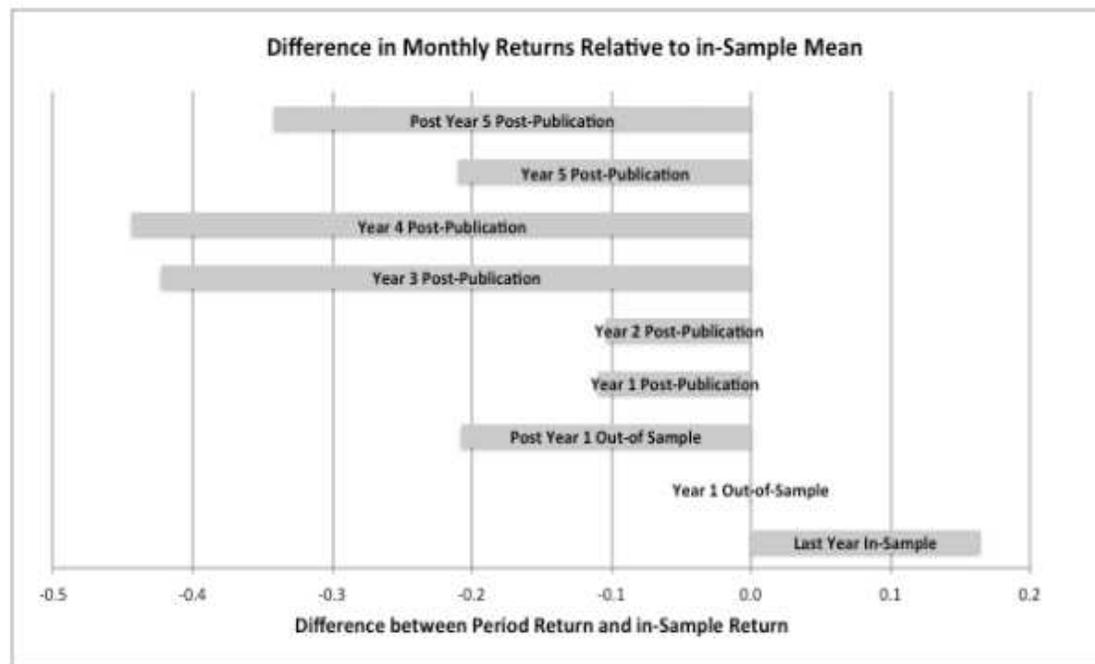
- Is the performance of factor strategies real?
- Publication bias due to complex agency problems (Harvey, 2017)
 - Journal editors compete for impact factors, tend to publish papers with the most significant results
 - Authors file away papers with weak/negative results, engage in “p-hacking”, selecting sample/test procedures until results become significant
 - The more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge” (Lo and MacKinlay, 1990)
- Robustness checks / new statistical tests are needed
 - Out of sample and sensitivity analysis (sample period, investment universe etc.)
 - More restrictive statistical tests

Data snooping

- Two prominent problems with traditional factor construction
- Factors' exposure to microcap stocks (Hou, Xue, and Zhang, 2017)
 - 60% stocks number, 3% market cap
 - Higher returns, larger cross sectional standard deviations: cross-sectional regressions (sensitive to outliers) of returns on factors assign high weights to microcaps
 - Equal-weight or NYSE-Amex-NASDAQ breakpoints **outweight microcaps**
 - Due to **high transaction costs**, anomalies in microcaps are more apparent than real
- With NYSE breakpoints and value weight, **64% of factors insignificant** at 5% level (85% at critical value of 3)
- Factors' redundancy
 - Large-scale replication of 447 anomalies with microcaps alleviated
 - Among the remaining 161 significant anomalies, the **q-factor model leaves 115 alphas insignificant**

Data snooping

- Factors' Alpha Decay
 - Post-publication tests of 97 anomalies (McLean and Pontiff, 2016): portfolio returns are 26% lower out-of-sample and 58% lower post-publication



- Impact of increased liquidity and trading activity: return to anomalies has halved after decimalization (Chordia et al., 2014)

Evaluating Data Snooping is Challenging

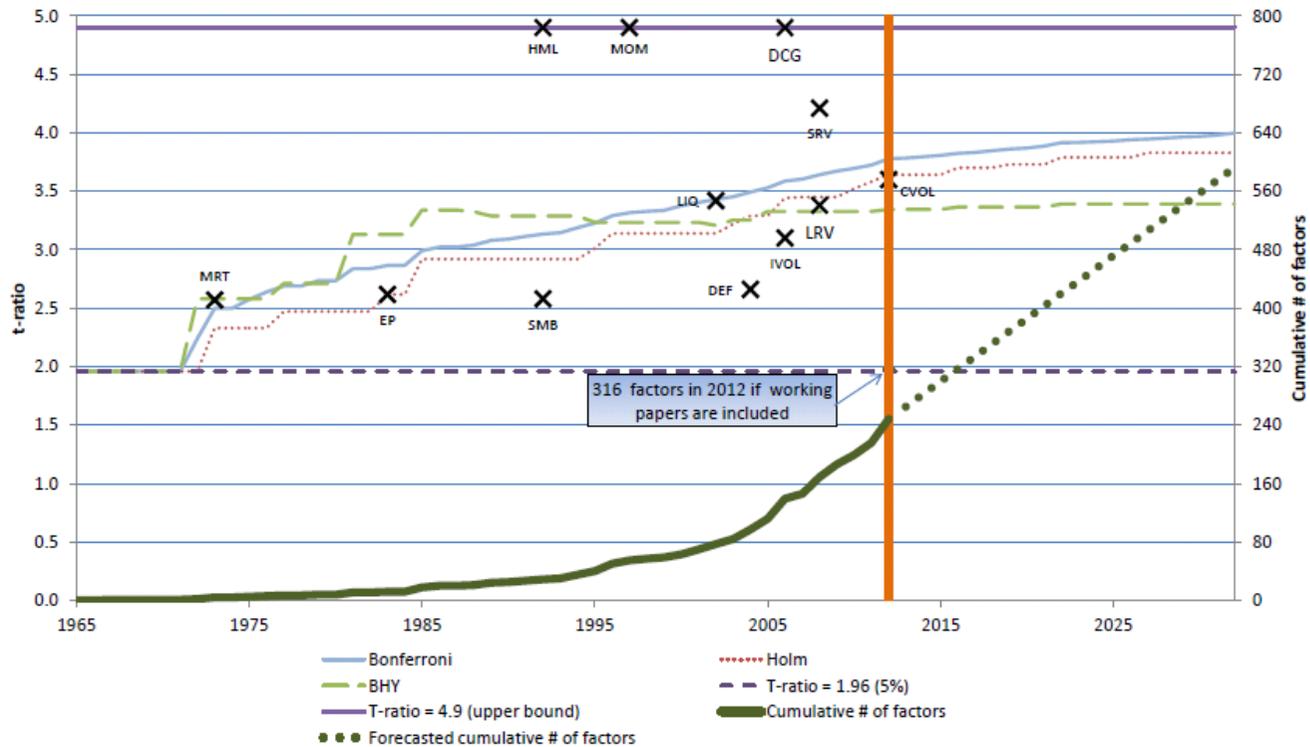
- Yan and Zheng (2017) compare “historic” factors with an artificial universe of 18 000 fundamental-based factors
 - Compare the distribution of t-stats for simulated factors with that of “historic” factors
 - **Size, idiosyncratic volatility, institutional ownership, analyst coverage** are not a product of data mining
- Chordia Goyal and Saretto (2017) compute the performance of 2.1 million of trading strategies
 - Imposing a tolerance of 5% of false discoveries and a significance level of 5%, they find that the critical value for alpha t-stat is 3.79
 - The **17 surviving factors lack economic underpinning !**
 - Ex: ratio of the difference between Total Other Liabilities and the value of Property Sales to the Number of Common Shares

More Restrictive Tests

- Multiple testing framework controlling for false-discovery rate (Harvey et al., 2014)
 - Given so many papers have attempted to explain the same cross-section of expected returns, statistical inference should not be based on a single test
 - They propose to use a **multiple testing framework** to control for *false-discovery rate*, commonly used in the medical literature
 - 3 types of statistical adjustments to the test: (1) Bonferroni, (2) Holm to account for family-wise error rate (probability of even a single false discovery, whatever the number of tests), (3) Benjamini, Hochberg and Yekutieli (BHY)

More Restrictive Tests

- Many discovered factors do not pass the adjusted thresholds



MRT: market beta (Fama and McBeth, 73) ; EP : earnings-price ratio (Basu, 83) ; DCG: durable consumption good (Yogo, 2006) ; DEF: default likelihood (Vassalou and Xing, 2004) ; LRV : long run volatility (Adrian and Rosenberg, 2008) ; CVOL : consumption volatility (Boguth and Kuehn, 2012)

Back to Basics: Competing Factor Models

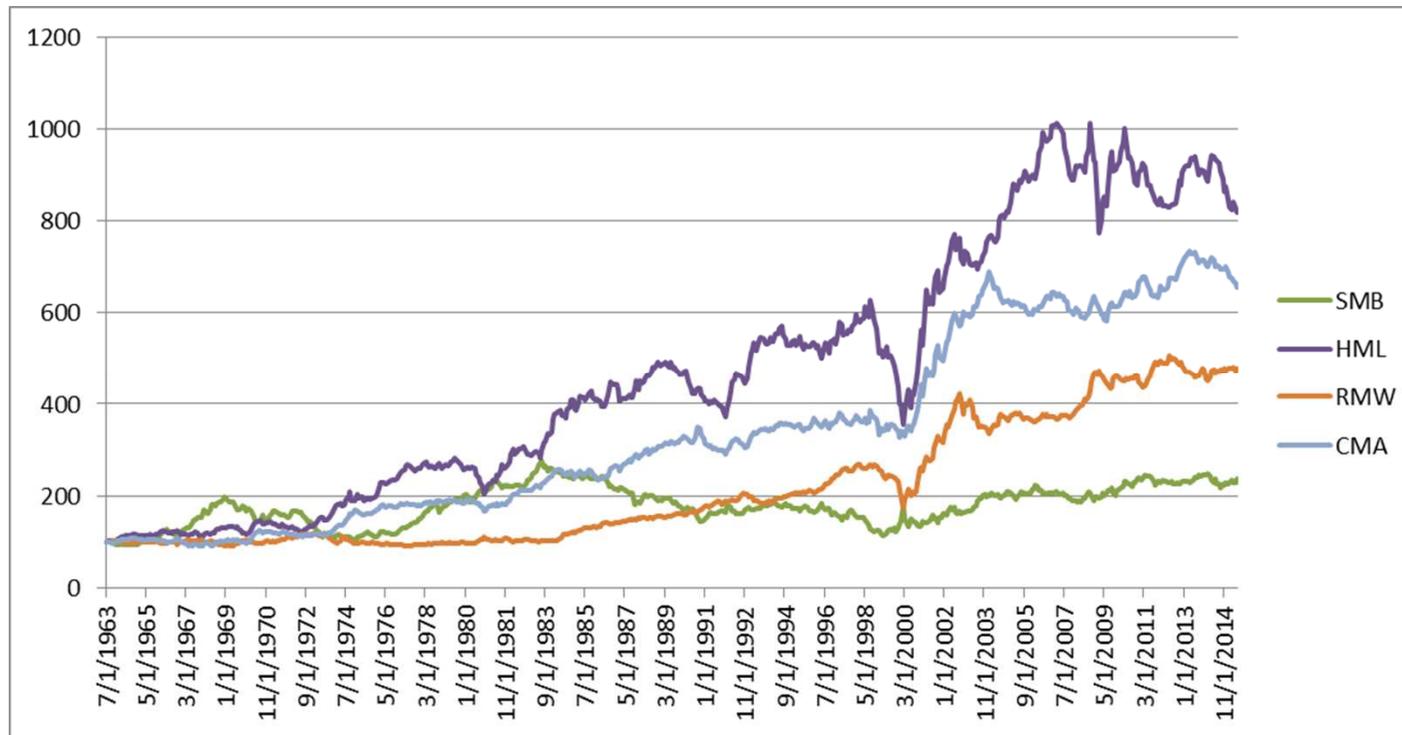
- Hou Xue and Zhang (2015) q-factor model
 - 4 factors: market, size, investment and profitability (ROE)

$$E[R_i] - R_f = \beta_{\text{MKT}}^i E[\text{MKT}] + \beta_{\text{ME}}^i E[r_{\text{ME}}] + \beta_{\text{I/A}}^i E[r_{\text{I/A}}] + \beta_{\text{ROE}}^i E[r_{\text{ROE}}]$$

- Compare the performance of the q-factor model to the Fama-French 3-factor and 5-factor models, the Carhart (1997) model, the Pastor-Stambaugh (2003) model with liquidity factor, the Jagannathan-Wang (2007) 4th-quarter consumption growth model, the Adrian-Etula-Muir (2014) financial intermediary leverage factor model.
- In factor spanning tests, the q-factors capture the new Fama-French factors, but the converse is not true.

Back to Basics: Competing Factor Models

- Fama and French (2014) propose a new 5-factor model
 - Market, Size (SMB), Value (HML), Profitability (Robust Minus Weak, RMW) and Investment (Conservative Minus Aggressive, CMA)



Source: Kenneth French, author's calculations

Back to Basics: Competing Factor Models

- Fama and French (2014) value factor is redundant to profitability and investment
 - Result of the regression of each factor on the other four

Table 1

	Intercept	RM-RF	SMB	HML	RMW	CMA	R ²
RM-RF	9.8% (4.94)		0.25 (4.45)	0.03 (0.37)	-0.40 (-4.84)	-0.91 (-7.82)	24%
SMB	4.6% (3.22)	0.13 (4.45)		0.05 (0.81)	-0.48 (-8.42)	-0.17 (-1.92)	18%
HML	-0.5% (-0.46)	0.01 (0.37)	0.02 (0.81)		0.23 (5.39)	1.04 (23.04)	52%
RMW	5.2% (5.44)	-0.09 (-4.84)	-0.22 (-8.42)	0.20 (5.39)		-0.44 (-7.85)	22%
CMA	3.3% (5.03)	-0.10 (-7.82)	-0.04 (-1.92)	0.45 (23.04)	-0.21 (-7.85)		57%

Source: AQR Capital Management, LLC

Back to Basics: Competing Factor Models

- AQR's 6-factor model
 - Add the momentum (UMD) factor
 - Change the value factor for HML-DEV (see Asness and Frazzini, 2013 "The Devil is in HML's detail") : book value with 6M lag but price with no lag, monthly rebalancing
 - They also propose a new "quality" factor

	Intercept	RM-RF	SMB	HML-DEV	RMW	CMA	UMD	R ²
RM-RF	10.8% (5.32)		0.25 (4.55)	-0.03 (-0.31)	-0.37 (-4.55)	-0.85 (-7.86)	-0.13 (-2.25)	25%
SMB	4.0% (2.73)	0.13 (4.55)		0.07 (1.16)	-0.47 (-8.53)	-0.17 (-2.15)	0.06 (1.45)	18%
HML-DEV	4.9% (4.74)	-0.01 (-0.31)	0.03 (1.16)		0.07 (1.61)	0.89 (20.01)	-0.52 (-27.32)	68%
RMW	4.7% (4.61)	-0.09 (-4.55)	-0.23 (-8.53)	0.06 (1.61)		-0.29 (-5.26)	0.07 (2.43)	19%
CMA	1.4% (1.94)	-0.11 (-7.86)	-0.04 (-2.15)	0.45 (20.01)	-0.15 (-5.26)		0.22 (12.24)	52%
UMD	9.2% (6.32)	-0.07 (-2.25)	0.06 (1.45)	-1.07 (-27.32)	0.14 (2.43)	0.90 (12.24)		57%

Source: AQR Capital Management, LLC

Interpreting Factors: Risk or Behavioral Anomalies?

- A risk factor rewards a “true” risk taken by investors
 - Ex: size (small stocks more risky than large stocks), value (distressed stocks)
- It is an anomaly if the premium can only be explained by investors’ behavior or mispricing (limits to arbitrage)
 - Ex: momentum stocks, low vol, quality stocks (Piotroski, 2000)
- In practice, many risk premia have behavioral explanations or are related to mispricing (Yuan and Zheng, 2017)

Interpreting Factors: Risk or Behavioral Anomalies?

- Charoenruek and Conrad (2005): a risk factor should demonstrate a positive relationship between conditional mean and variance of the return
 - **Size value and liquidity** factors can be considered a priced risk, not **momentum**
- Pukthuanthong and Roll (2014): a factor candidate must be related to the principal component of a covariance matrix of returns
- De Miguel et al. (2018): factors should matter jointly from a portfolio perspective
 - Use a bootstrap method to test which characteristics have **parametric portfolio weights** significantly different from zero
 - Six characteristics: **unexpected quarterly earnings, return volatility, asset growth, momentum, profitability, beta**, are significant

Interpreting Factors: Risk or Behavioral Anomalies?

- Fama and French (2018)
 - Recognize that most previous work uses a “**left-hand side**” approach: focusing on **unexplained returns** (alpha)
 - Propose to use a “**right-hand side**” approach: spanning regressions where each factor candidate is regressed on the model’s other factors
 - Test if multiple factors add to a base model using the performance metric of Barillas and Shanken (BS 2016) and the Gibbons, Ross, and Shanken (GRS 1989) statistic
 - The winning factor model has **size, and the small components of value, profitability, investment and momentum**

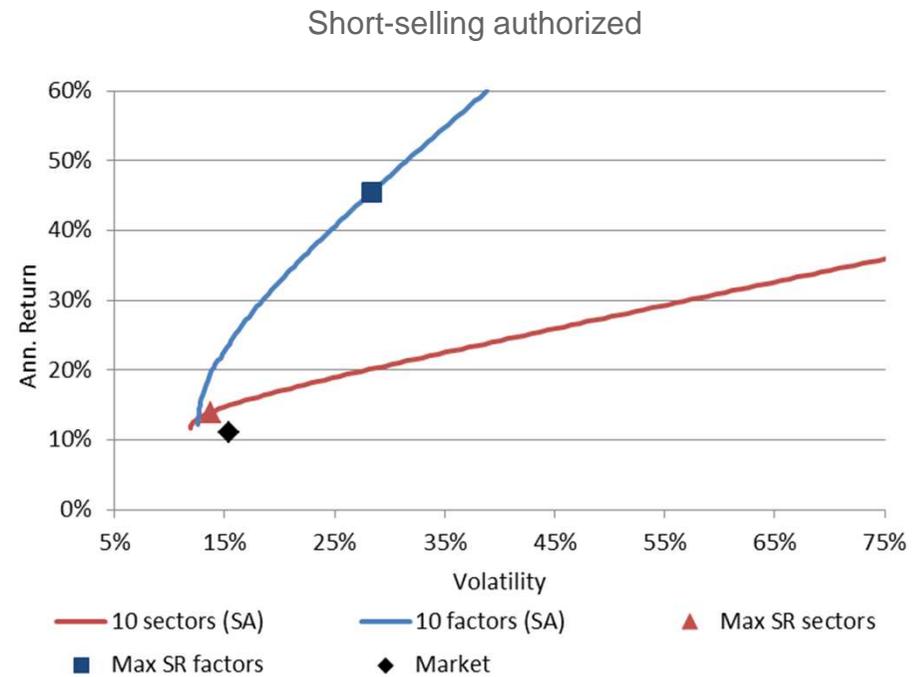
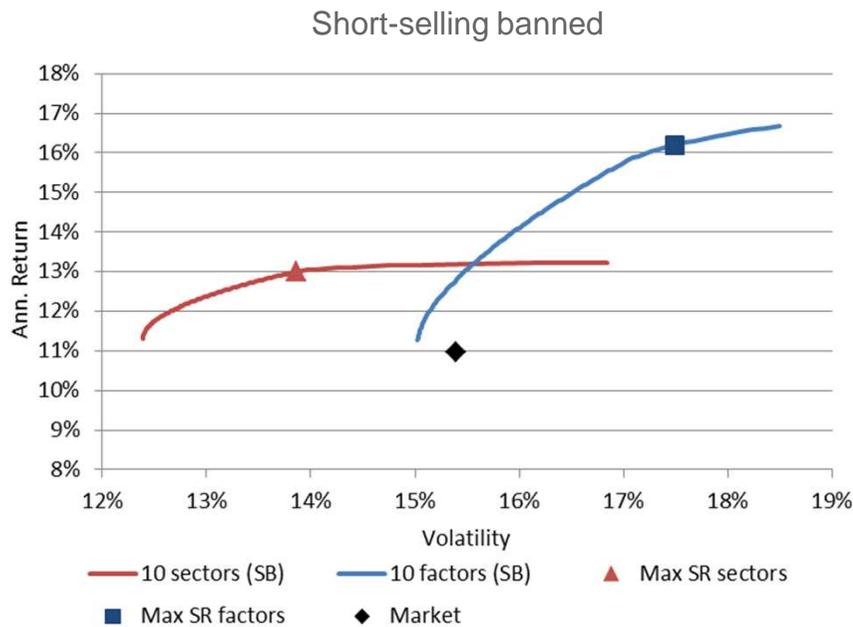
Factor Investing: A New Paradigm?

Key Questions

- Identifying Risk Factors
 - Factor proliferation and data snooping
 - Back to Basics: competing factor models
 - Risk factors or anomalies?
- **Factor Investing: A New Paradigm?**
 - **Factor diversification**
 - **Factors long-only or long-short?**
 - **Factor mix or stock selection across multiple characteristics?**
 - **Factor timing: Is it worth it?**
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Factor Diversification

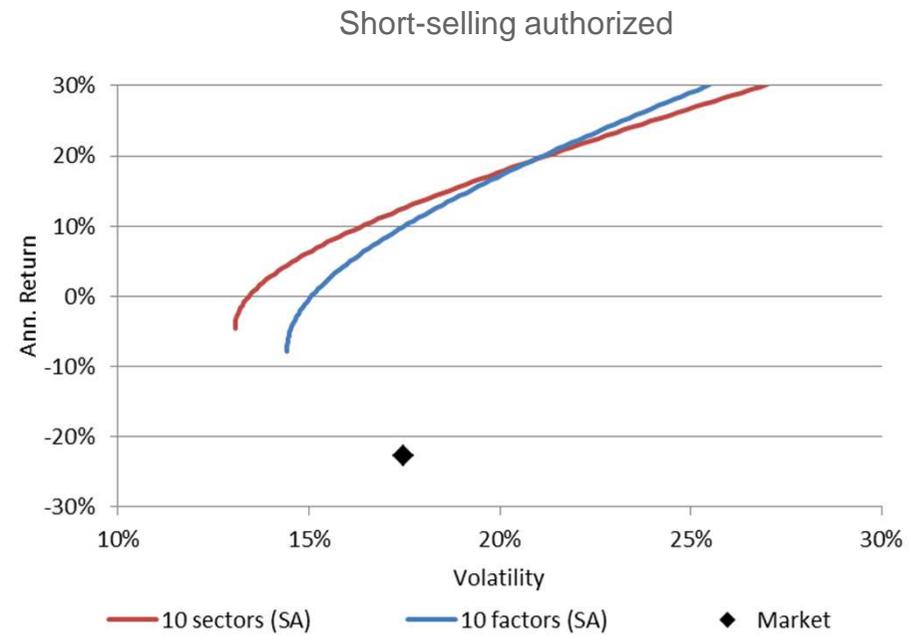
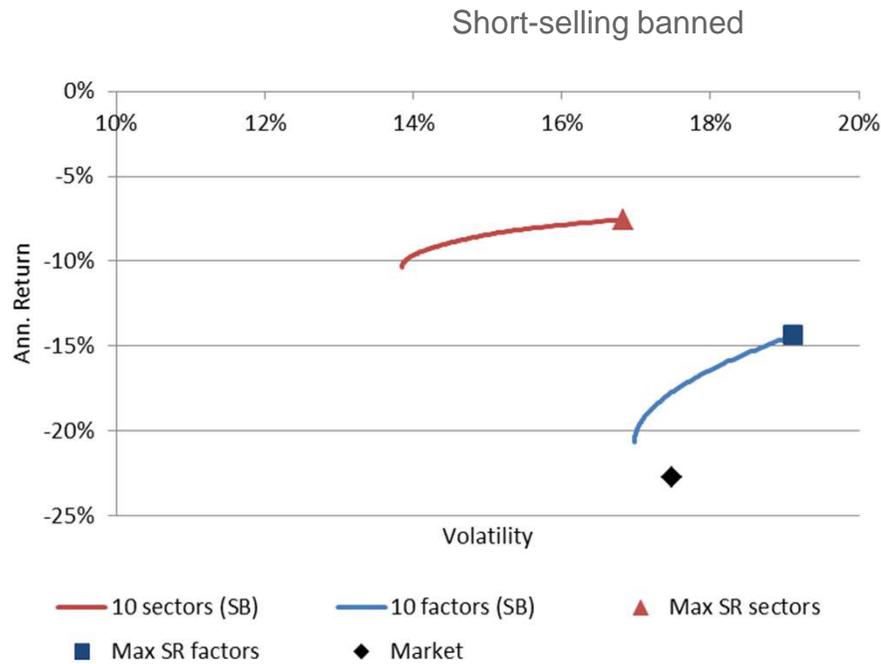
- Combining factors improves on the market
 - Optimal factor and sector portfolios, full sample 1963-2015



Source: Brière et Szafarz (2017a)

Factor Diversification

- Be careful with crises times
 - Optimal factor and sector portfolios, bear markets



Source: Brière et Szafarz (2017a)

Factor Diversification

- Brière and Szafarz (2017a) compare optimal portfolios of factors and sectors across multiple performance measures

- **Vertical & horizontal distances** between the market and efficient frontier (Basak et al., 2002; Brière et al., 2013)

- **Jensen's alphas and Sharpe ratios**

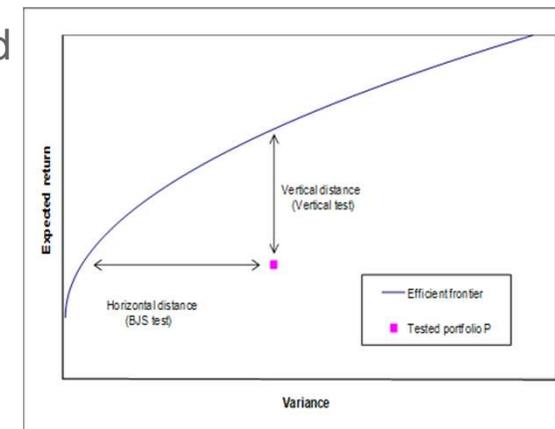
Wald test (+Newey-West correction) of equality

Ledoit and Wolf (2008) test of equality

- **Certainty Equivalent Returns (CER)**

Christoffersen and Langlois (2013) bootstrapped test of equality, CRRA, CARA utility

Manipulation-proof performance measure (Goetzmann et al., 2007)



Factor Diversification

- Factors: return improvement, sectors: risk reduction
 - Vertical and horizontal distance to the market portfolio

short-selling banned

Sample	Panel A: Vertical distance (exp. returns)	
	Sectors	Factors
	Full sample	0.0017*
Bear markets	-	0.0394***
Bull markets	0.0006	0.0003*
Recessions	0.0069***	-
Expansions	0.0013	0.0017***
Panel B: Horizontal distance (variance)		
Full sample	-	-
Bear markets	-	-
Bull markets	0.0001***	0.00002*
Recessions	-	-
Expansions	0.0005***	0.00004

short-selling authorized

Sample	Panel A: Vertical distance (exp. returns)	
	Sectors	Factors
	Full sample	0.0032**
Bear markets	0.0303	0.0272***
Bull markets	0.0007	0.0037***
Recessions	0.0282***	0.0323***
Expansions	0.0019*	0.0076***
Panel B: Horizontal distance (variance)		
Full sample	-	-
Bear markets	-	-
Bull markets	0.0001***	0.0003***
Recessions	-	-
Expansions	0.0005***	0.0004***

Source: Brière et Szafarz (2017a)

Factor Diversification

- Accounting for extreme risks, no significant difference between factor/sector portfolios when short-selling banned (CER)

Portfolio	Low risk aversion			Medium risk aversion			High risk aversion		
	CER (CRRA)		Bootstrapped equality t-test	CER (CRRA)		Bootstrapped equality t-test	CER (CRRA)		Bootstrapped equality t-test
	$\gamma = 5$			$\gamma = 10$			$\gamma = 15$		
	Sectors	Factors		Sectors	Factors		Sectors	Factors	
In-sample estimation									
<i>LOmaxSR</i>	0.67	0.65	0.05	0.20	-0.25	1.03	-0.38	-1.57	1.52
<i>LOminvol</i>	0.62	0.45	0.69	0.27	-0.13	1.33	-0.10	-0.84	1.77*
<i>Equalweigh.</i>	0.52	0.36	0.53	-0.02	-0.52	1.18	-0.69	-1.74	1.44
Out-of-sample estimation, M=60 months									
<i>LOmaxSR</i>	0.36	0.51	-0.47	-0.28	-0.34	0.14	-1.04	-1.51	0.69
<i>LOminvol</i>	0.61	0.47	0.54	0.26	-0.18	1.26	-0.13	-1.05	1.64*
<i>Equalweigh.</i>	0.48	0.26	0.67	-0.09	-0.66	1.26	-0.80	-1.93	1.44
Out-of-sample estimation, M=120 months									
<i>LOmaxSR</i>	0.33	0.66	-0.93	-0.39	-0.23	-0.33	-1.26	-1.46	0.24
<i>LOminvol</i>	0.70	0.56	0.50	0.35	-0.11	1.28	-0.02	-1.03	1.73*
<i>Equalweigh.</i>	0.56	0.39	0.46	-0.03	-0.56	1.06	-0.78	-1.91	1.27

risk-free rate that would make the investor indifferent between holding the risky portfolio made of factors/sectors and earning the CER (CRRA Utility)

γ is the level of risk aversion of the Constant Relative Risk Aversion (CRRA) utility function

Source: Brière et Szafarz (2017a)

Factor Diversification

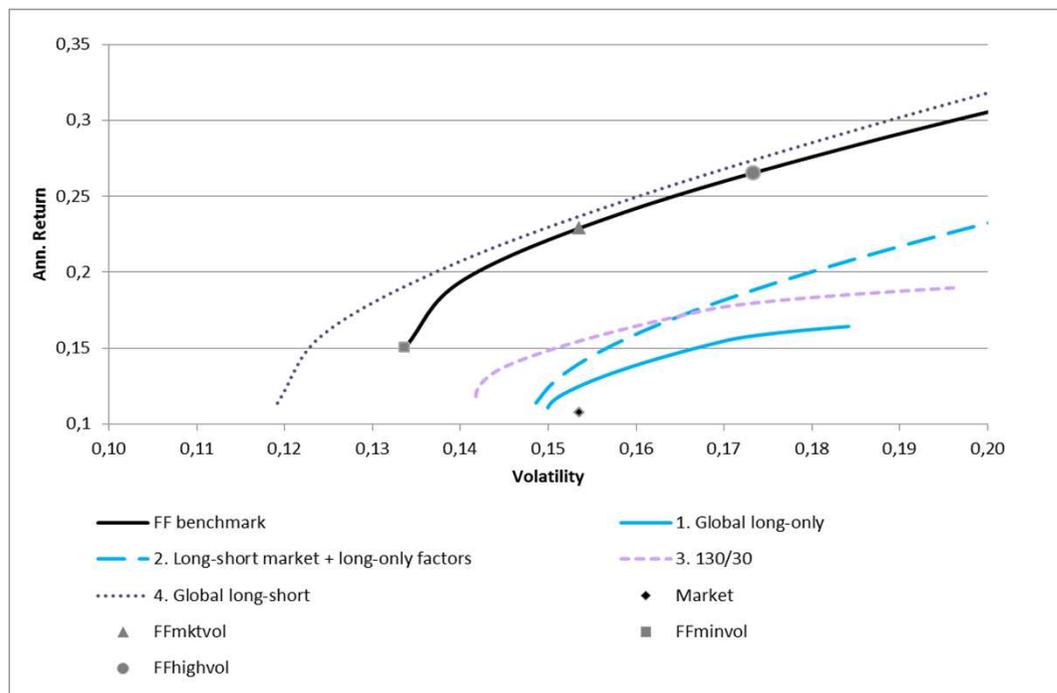
- Factor optimal portfolios beat sectors for low risk averse investors when short-selling is authorized (CER)

Portfolio	Low risk aversion			Medium risk aversion			High risk aversion		
	CER (CRRA)		Bootstrapped equality t-test	CER (CRRA)		Bootstrapped equality t-test	CER (CRRA)		Bootstrapped equality t-test
	$\gamma = 5$			$\gamma = 10$			$\gamma = 15$		
	Sectors	Factors		Sectors	Factors		Sectors	Factors	
In-sample estimation									
<i>LOmaxSR</i>	0,77	2,07	-3,09***	0,34	-0,16	0,71	-0,13	-3,37	2,58***
<i>LOminvol</i>	0,68	0,67	0,05	0,36	0,28	0,32	0,02	-0,19	0,64
Out-of-sample estimation, M=60 months									
<i>LOmaxSR</i>	-	-	-	-	-	-	-	-	-
<i>LOminvol</i>	0,66	0,78	-0,5	0,3	0,38	-0,3	-0,08	-0,07	0
Out-of-sample estimation, M=120 months									
<i>LOmaxSR</i>	-	-	-	-	-	-	-	-	-
<i>LOminvol</i>	0,75	0,82	-0,3	0,41	0,43	0	0,05	0	0,18

Source: Brière et Szafarz (2017a)

Factors Long-Only or Long-Short?

- Long-Short Multi-Factor Extensions are Attractive
 - Efficient Frontiers (1963-2015)



- But be carefull of **shorting costs** (Huij et al., 2014)

Source: Brière et Szafarz (2017b)

Selecting Stocks across Multiple Characteristics

- What is best: Portfolio mix of factors or stock selection across multiple characteristics?
 - Mix: combine separate long-only portfolios for each individual style
 - Integrate: create an aggregate ranking of stocks to build a multi-style portfolio

- Largest multi-factor ETFs (Aug 2017) use both approaches

Name	Asset Manager	AuM	Inception	Approach
Goldman Sachs ActiveBeta U.S. Large Cap Equity ETF	Goldman Sachs	\$1.15B	01/28/15	mix
FlexShares Morningstar US Market Factor Tilt Index Fund	FlexShares	\$842.43M	09/16/11	integrate
John Hancock Multifactor Large Cap ETF	John Hancock	\$236.27	09/28/15	integrate
State Street Multi-Factor Global Equity Fund	State Street	\$126.39	09/30/14	mix
iShares Edge MSCI Multifactor USA ETF	iShares	\$110.03M	04/30/15	integrate
JPMorgan Diversified Return U.S. Equity ETF	JP Morgan	\$81.15M	09/29/15	integrate
The Global X Scientific Beta US ETF	Global X	\$67.18M	05/12/15	mix
Franklin LibertyQ Global Equity ETF	Franklin	\$26.19M	06/01/16	integrate
ETFS Diversified-Factor U.S. Large Cap Index Fund	ETF Securities	\$7.82M	01/28/15	mix

Source: Leippold and Rueegg (2017)

Selecting Stocks across Multiple Characteristics

- Selecting stocks across characteristics leads to better results
 - Clarke et al. (2016): the mixed approach captures one-half of the potential improvement over the market Sharpe ratio.
 - Bender and Wang (2016): integration leads to a superior risk–return trade-off due to the fact that it captures nonlinear cross-sectional interaction effects between factors.
 - Fitzgibbons et al. (2016): the integrated approach applied to long-only portfolio is more profitable: allows to reach higher exposure to styles, trades can net out, reducing transaction costs
- Leippold and Rueegg (2017) apply a multiple hypothesis framework (adjusting for the number of portfolios tried) and find no significant differences

Factor Timing: Is it Worth It ?

- Difficulty of factor timing (Asness, 2016)
- Valuation matters
 - The **value factor** performs better when **cheaper than normal** (Asness et al., 2000)
 - **Value spread** = difference between value (e.g. BTM) signal of long vs short portfolio
 - True for other factors (Cohen et al., 2003; Arnott et al., 2016; Baba-Yara et al., 2018)
- Volatility matters
 - Volatility predicts momentum returns negatively (Barroso and Santa-Clara, 2015), also true for other factors (Moreira and Muir, 2017, Barroso and Maio, 2018)
 - Scale the long-short portfolio by its previous 6M realized volatility to target constant volatility, Sharpe ratio improves, strong **reduction in crash risk.**
- Fundamentals matter (Dichtl et al., 2017 ; Miller et al., 2015 ; Aretz et al., 2010; Bartram and Grinblatt, 2018)

What Next ?

Key Takeaways

- Factors should be carefully selected
- They should be combined for long term asset strategic asset allocation
- They should ideally be played long-short
- They can be timed
- Factors are for low to moderate risk-averse investors

Further Questions

- Factor transaction costs
 - No consensus (Novy-Marx and Velikov, 2014 ; Korajczyk and Sadka, 2008, Frazzini et al., 2014)
 - Depends on portfolio size, breakeven capacity of each investment strategy.

- Factor crowding
 - Capital devoted to factor strategies increased since the 1990s (Hanson and Sunderam, 2011)
 - Mutual funds flows (“dumb money”) **exacerbate stock return anomalies**, while hedge funds flows (“smart money”) attenuates them (Akbas et al., 2014).
 - Crowding explains **negative skewness** in momentum returns (Lou and Polk, 2013 ; Huang, 2015) and negatively predicts mean returns (Barroso et al., 2017)

- Factors in other markets than equities (Asness et al., 2013 ; Beekhuizen et al., 2016, etc.)



— MENTIONS LEGALES

Société Anonyme au capital social de 1 086 262 605 euros
Société de Gestion de Portefeuille agréée par l'AMF sous le n° GP 04000036
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