STOCK MARKET ANOMALIES

AALTO UNIVERSITY

2019

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Part II

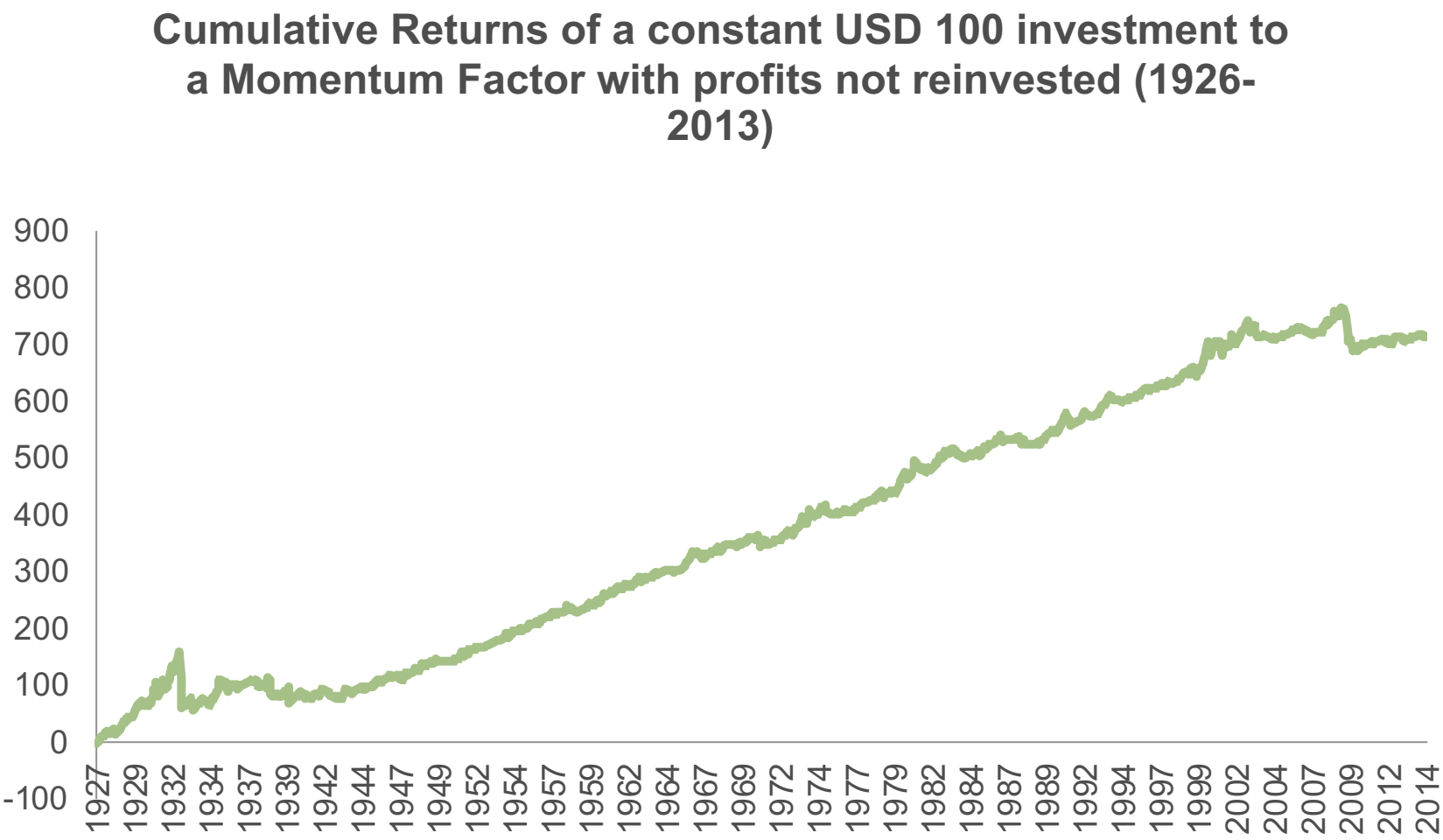
- Momentum factor
- Value Factor
- Other anomalies
- Market correcting forces
- Summary

Momentum

- Sort stocks by their 2 to 12 month returns
- Invest in winners and short the losers
- Skip one month
- Hold one to 12 months

- Extremely attractive up to 12% pa returns for such long-short portfolios

Momentum Factor is a long-short zero investment portfolio that is long (short) in the stocks that have performed best (worst) in the past 2 to 12 months. For more details see Kenneth French's website.



POSSIBLE EXPLANATIONS

MOMENTUM STRAGEGY

• Jegadeesh and Titman (1993): Returns for buying winners and selling loosers: Implications for stock market efficiency (1993). Moskowitz and Grinblatt (1999) show this is largely due to industry momentum.

•Why? Different theories:

- Investors' herding? Implications?
- Information spreads slowly, trend followers try to learn from price moves (Hong and Stein)? Implications?
- Momentum follows when risk is proportional to Value (for instance when some stocks value increases, its risk in its investors portfolio increases, implying an increased risk premium). Implications? See Cochrane, Longstaff and Santa-Clara, 2008.
- Momentum can also arise from behavioral biases, Daniel, Hirshleifer and Subrahmanyam 1998.

Hong and Stein (1993)

- Two types of investors
- First, news watchers with CARA utilities and Walrasian demand
- Liquidating dividend

$$D_T = D_0 + \sum_{j=0}^{T} \varepsilon_j$$

- Shocks ε_j decomposable to z subinnovations with variance σ^2 / z

$$\varepsilon_j = \varepsilon_j^1 + \varepsilon_j^2 + \varepsilon_j^3 + \ldots + \varepsilon_j^z$$

- z cohorts of investors who all see only one of the subinnovations each period, and a different one next period and so on…

Hong and Stein (1993)

In equilibrium, with only newswatchers it can be shown that

$$P_t = D_t + \left\{(z-1)\varepsilon_{t+1} + (z-2)\varepsilon_{t+2} + \ldots + \varepsilon_{t+z}\right\} / z - \theta Q$$

Here Q = supply and

Θ is product of parameter of risk aversion and $\sigma_{.}^{2}$

Note that in this setting prices adjust gradually to shocks.

Hong and Stein (1993)

- They add second class of traders who do not see signals but condition on the cumulative price change over k periods
- They invest with j period horizon
- With k = 1 we get (and momentum)

$$P_t = D_t + \left\{(z-1)\varepsilon_{t+1} + (z-2)\varepsilon_{t+2} + \ldots + \varepsilon_{t+z}\right\} / z - \theta Q - jA - \sum_{i=1}^{j} \phi(P_{t-1} - P_{t-2})$$

Information Percolation, Momentum and Reversal

Andrei and Cujean 2017 JFE

Combines the Grossman and Stiglitz model & Grossman and Miller model

- Supply shocks lead to reversals (as in Grossman and Miller)
- Information shocks and growing precision of signals leads to momentum (as price uncertainty declines)

Is Momentum Really Momentum□Robert Novy-Marx|

JFE 2012

Momentum is primarily driven by firms' performance 12 to seven months prior to portfolio formation, not by a tendency of rising and falling stocks to keep rising and falling. Strategies based on recent past performance generate positive returns but are less profitable than those based on intermediate horizon past performance, especially among the largest, most liquid stocks. These facts are not particular to the momentum observed in the cross section of US equities. Similar results hold for momentum strategies trading international equity indices, commodities, and currencies.

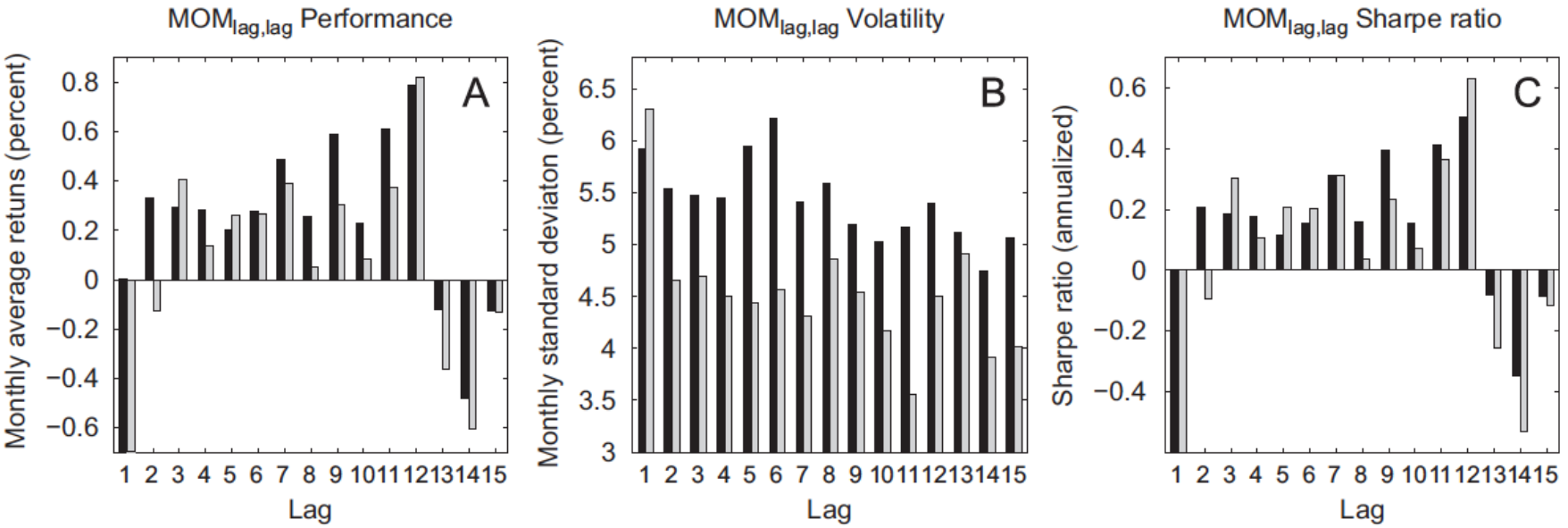


Fig. 1. Marginal strategy performance. This figures shows the average monthly returns (Panel A), monthly standard deviations (Panel B) and annual Sharpe ratio (Panel C) to winners-minus-losers strategies. Winners and losers are defined as the top and bottom deciles of performance in a single month, respectively, starting lag months prior to portfolio formation. Dark bars show value-weighted results and light bars show equal-weighted results. Average monthly returns for the one month reversals are −1.04% (value-weighted) and −2.82% (equal-weighted). The sample covers April 1927 to December 2010.

An Institutional Theory of Momentum and Reversal, RFS, 2013

Dimitri Vayanos, Paul Woolley

A theory of momentum and reversal based on flows between investment funds.

Flows are triggered by changes in fund managers' efficiency, which investors either observe directly or infer from past performance.

Momentum arises if flows exhibit inertia, and because rational prices under-react to expected future flows. Reversal arises because flows push prices away from fundamental values. Besides momentum and reversal, flows generate comovement, lead-lag effects and amplification, with these being larger for high-idiosyncratic-risk assets. A calibration of the model using evidence on mutual-fund returns and flows generates sizeable Sharpe ratios for momentum and value strategies.

Implication that good value returns should follow good momentum returns, do they?

Time-series momentum

Calculate annualized variance for assets as

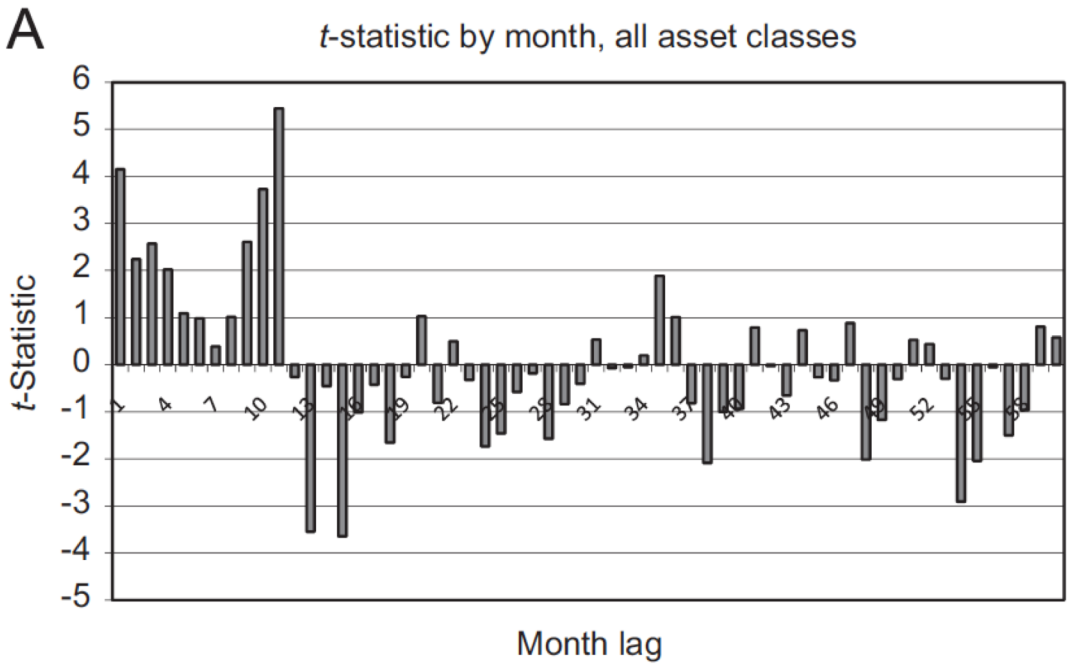
$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2$$

where $\bar{r}_t$ is the exponentially weighted average return. Here $\sum_{i=0}^{\infty} (1-\delta)\delta^i$ adds to one.

Time-series momentum

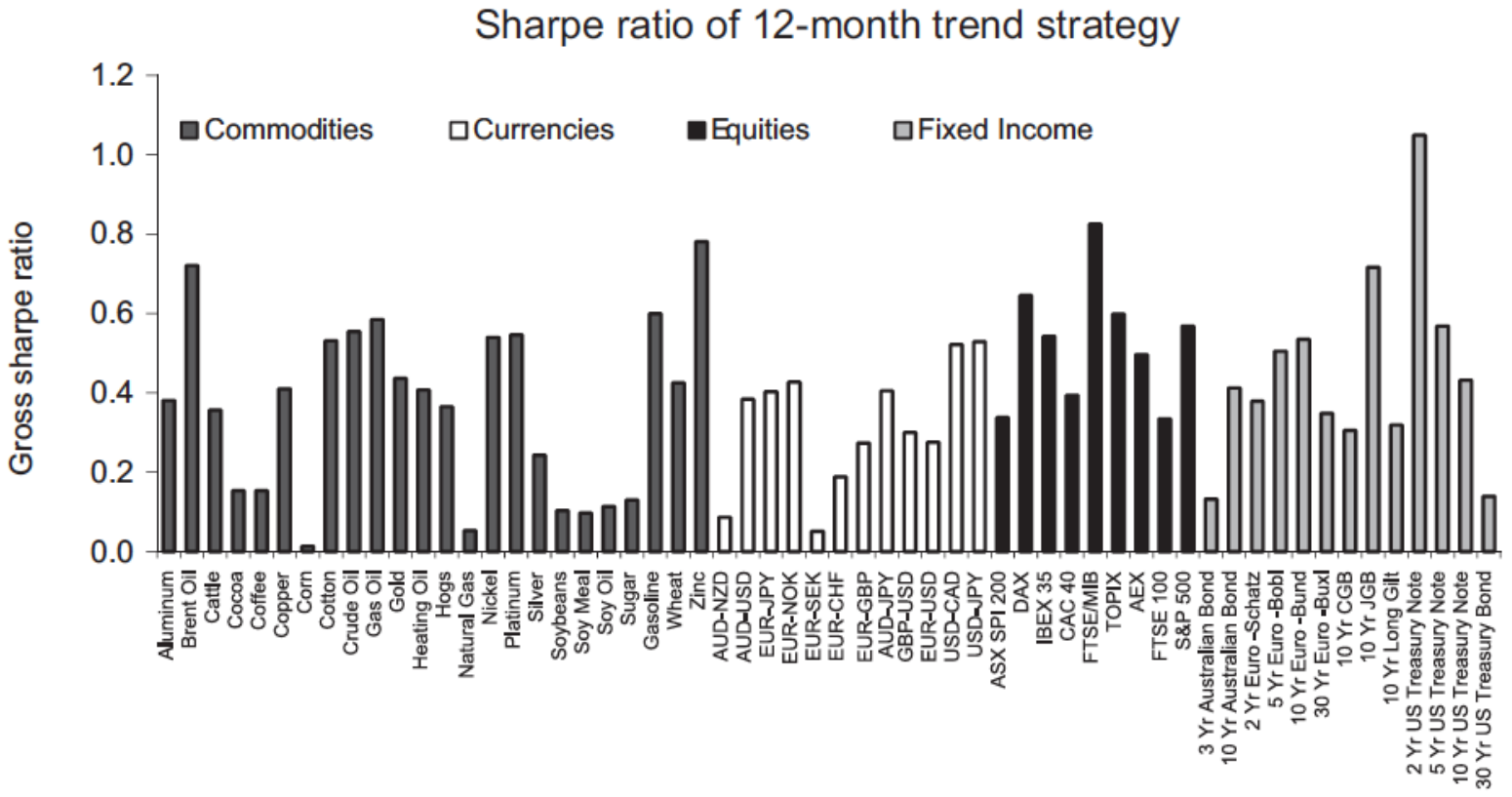
- Regressions to study the effect of past returns on future returns

$$r_t^s/\sigma_{t-1}^s = \alpha + \beta_h r_{t-h}^s/\sigma_{t-h-1}^s + \varepsilon_t^s$$

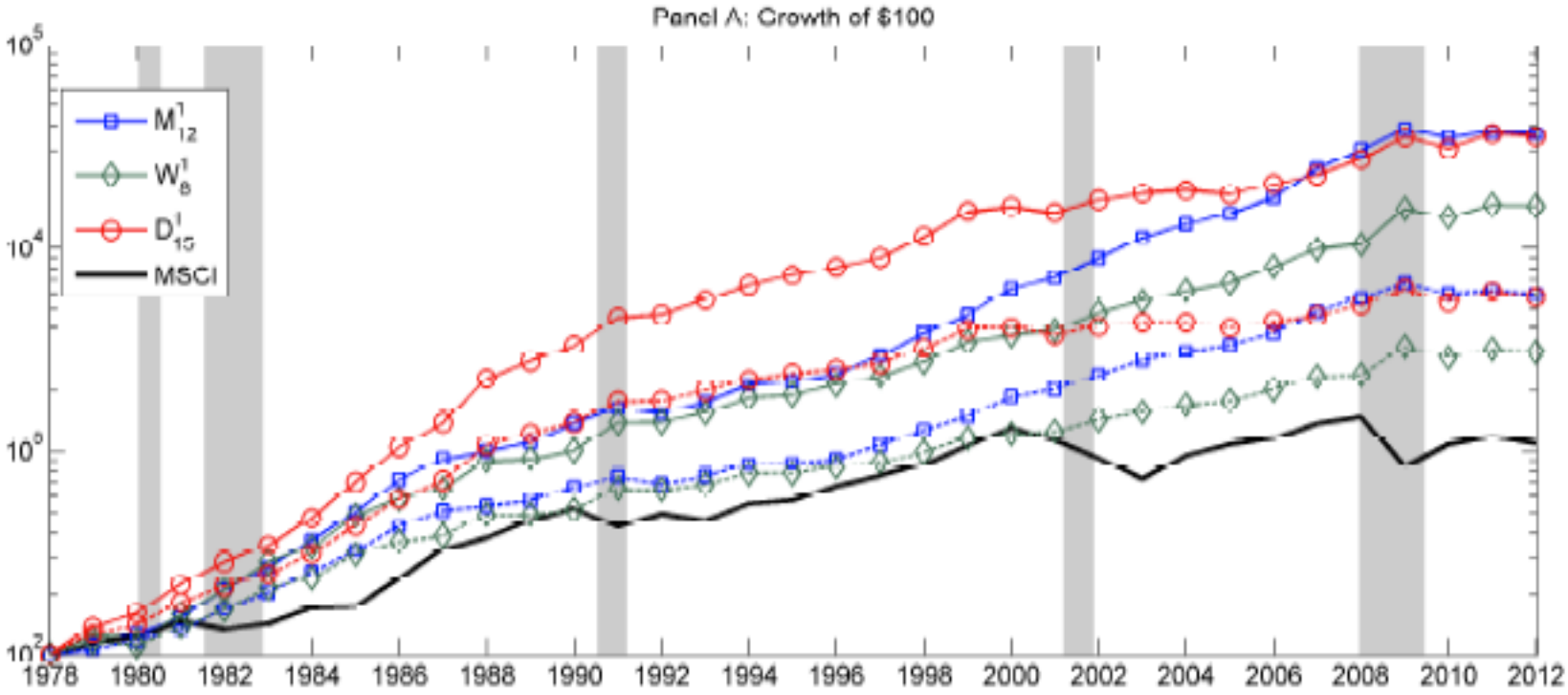


Go long (short) assets when 12-moth return positive (negative), making investment level inversely proportional to volatility

T.J. Moskowitz et al. / Journal of Financial Economics 104 (2012) 228–250



Baltas and Kosowski (2013) show evidence that CTA's (Commodity Trading Advisors) follow time-series momentum strategies and that the returns to Stock Index Futures based time-series momentum strategies (M = Monthly, W = weekly and D = Daily) are highly attractive (see below the returns to some such strategies – excluding fees and net of fees - along with the returns to MSCI index)



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Missing risk factors?

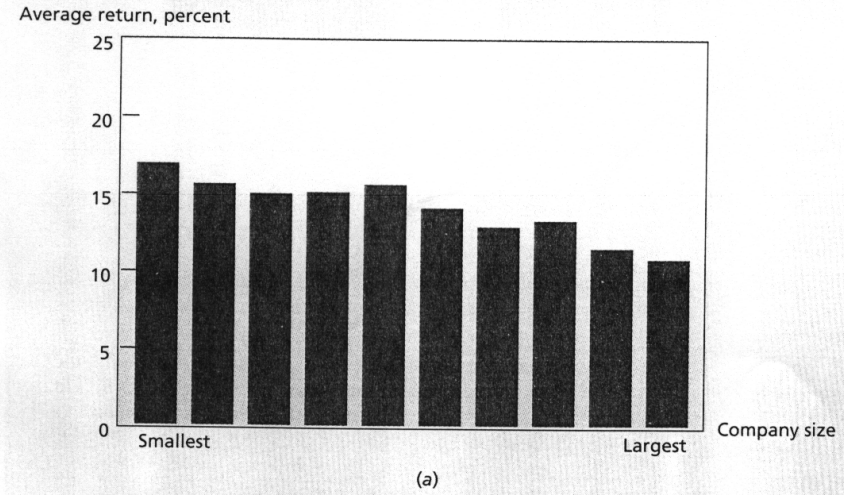


Figure 8-12 (*a*) Since the mid-1960s, stocks of small companies have done systematically better than stocks of large companies. (*b*) Stocks with low ratios of price to book value per share have done better than stocks with high price-to-book ratios. [*Source:* G. Fama and K. French, "The Cross-Section of Expected Stock Returns," *Journal of Finance,* **47**:427–465 (June 1992).]

Is value a risk factor or due to misvaluation

•Kokkonen and Suominen (2014) show that the HML value factor (the tradidional value factor based on sortings of market to book values) is closely related to a misvaluation factor. In a misvaluation factor we short stocks that appear most overvalued and invest in stocks that appear most undervalued. Fundamental values that are used to evaluate misvaluations are estimated using firms' book values and analysts' earnings forecasts.

•Misvaluation factor in combination with momentum gives extremely nice returns (Sharpe 0.7 p.a.)

•Asness, Pedersen and Moskovitz (2011) use 5-year past returns as measure of value.

Value spread forecasts value returns

- Cohen, Polk and Vuolteenaho (2003) look at the spread in P/B in the extreme 3 deciles of stocks sorted by P/B. This measure forecasts value stock returns.

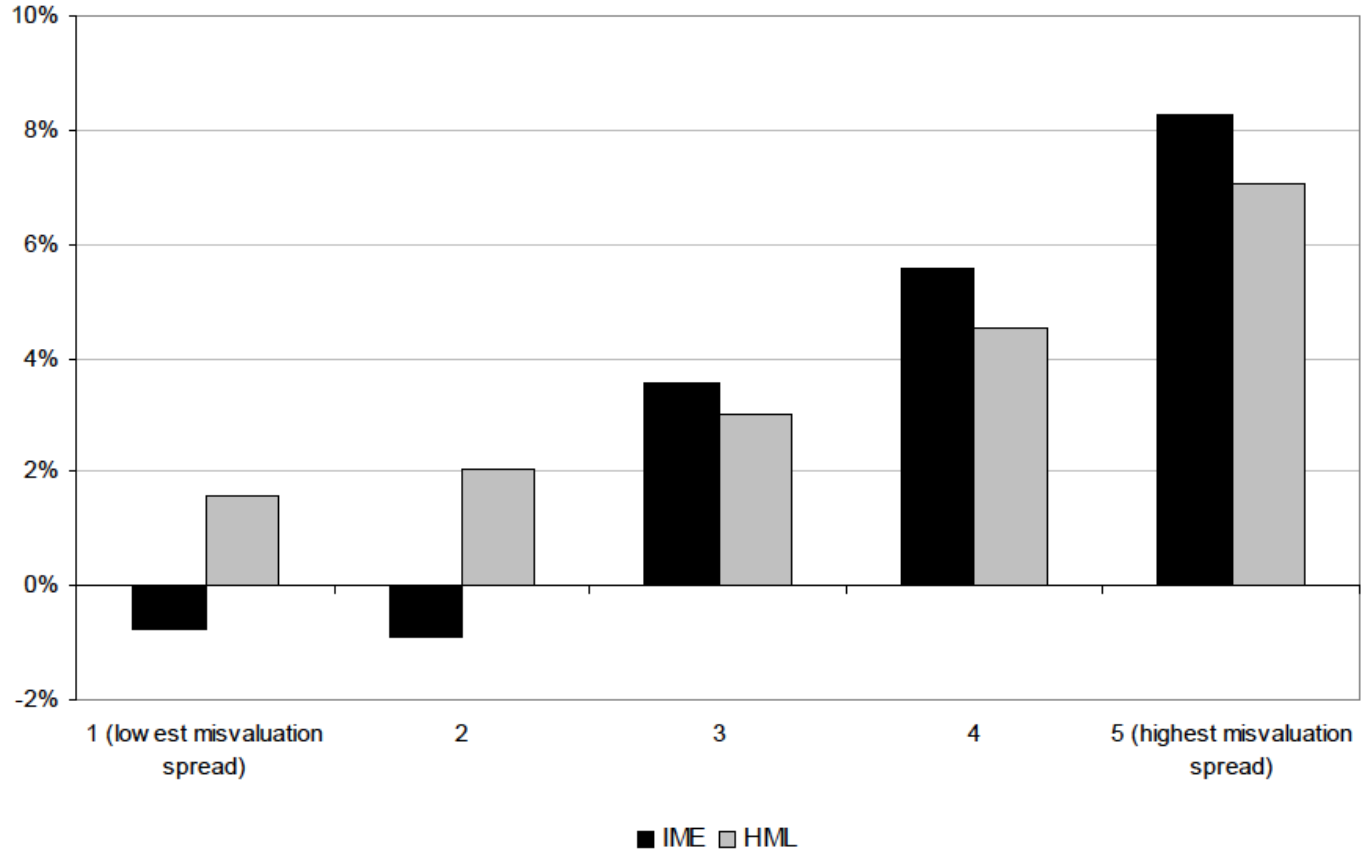
- Asness et al. (2000) use another refined measure of value spread to forecast returns.

- Similarly Kokkonen and Suominen (2014) calculate a misvaluation spread (the difference in misvaluation of the 3 extreme deciles of stocks sorted on misvaluation) and show this forecasts misvaluation based portfolio's returns.

IME = Inexpensive Minus Expensive =Misvaluation based long-short portfolio

Figure 4: Relation between Misvaluation, the Return on the IME Portfolio and the HML Factor

This figure plots the cumulative 12-months-ahead return on the IME portfolio (black bars) and the Fama and French (1993) HML factor (grey bar) conditional on the level of total misvaluation in the previous month. The groups are determines by dividing the misvaluation series into quintiles, with group 1 representing the lowest levels of misvaluation (spread), and group 5 representing the highest values of misvaluation.

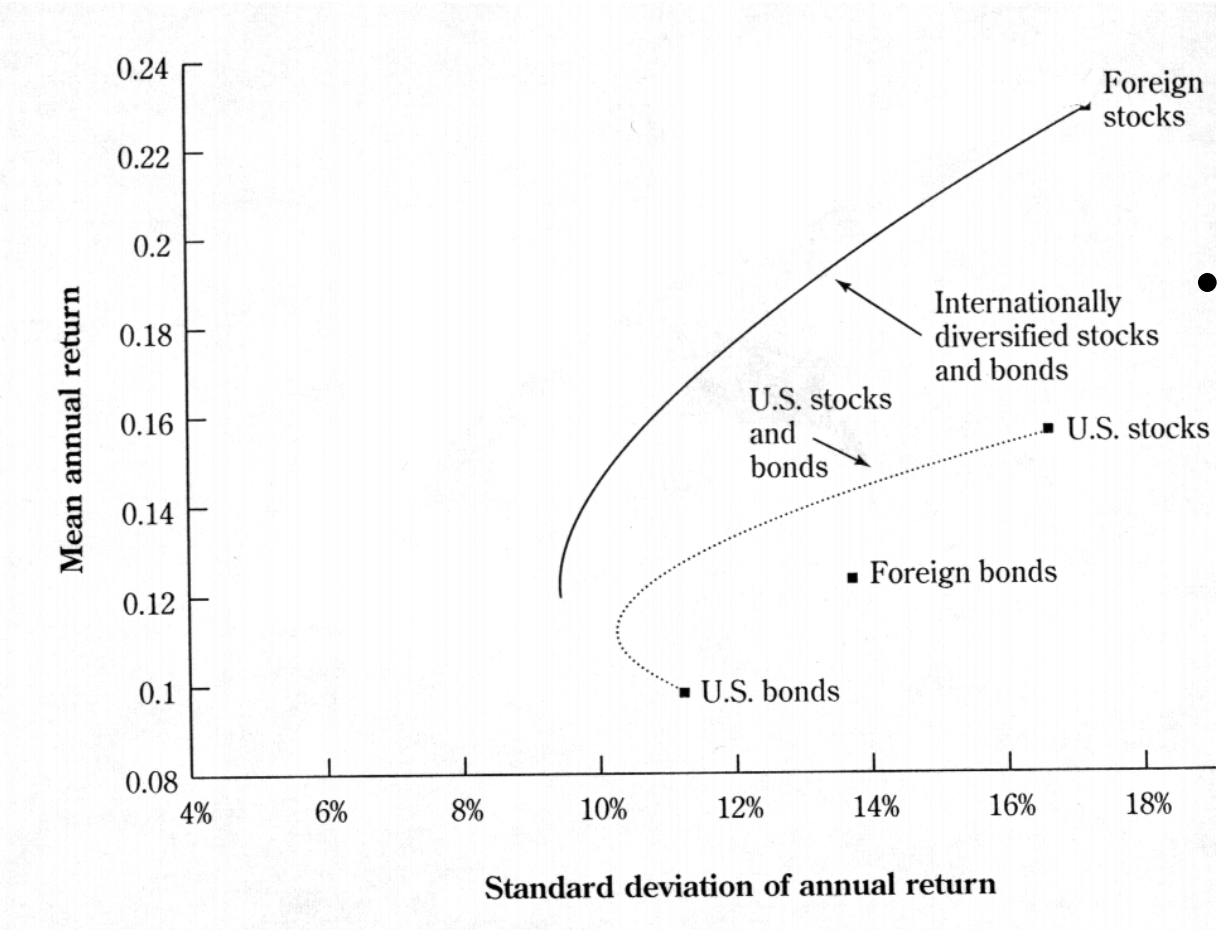


Misvaluation Spread

Portfolio considerations

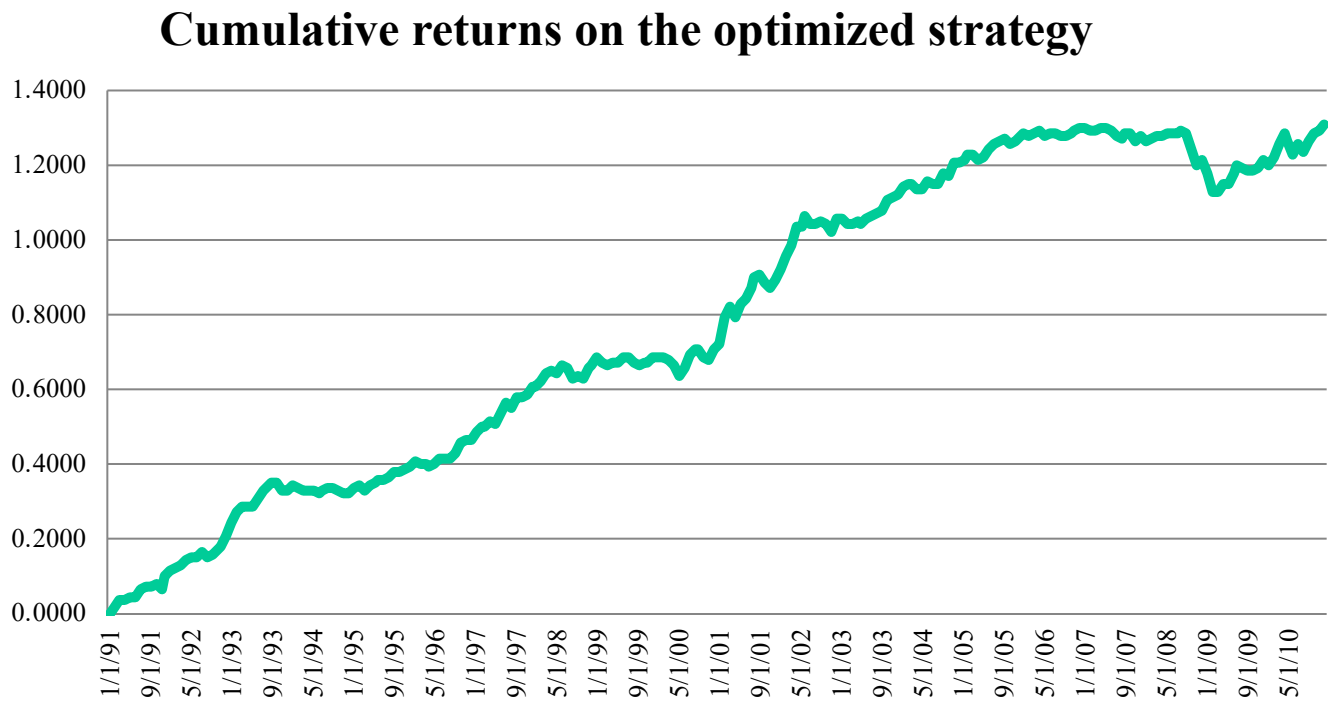
How attractive portfolios can we construct from momentum, size and value factors, combining them with equity portfolio and conditioning our investments on the level of value spread?

Traditional approach – combine stocks and bonds internationally.



Why not add value and momentum and make the level of investment in them time varying and conditional to value spread

It seems that such portfolios have very attractive returns – Somehow these factors work well in combination



Value and Momentum Everywhere

Clifford S. Asness, Tobias J. Moskowitz, and Lasse H. Pedersen

Abstract

Value and momentum ubiquitously generate abnormal returns for individual stocks within several countries, across country equity indices, government bonds, currencies, and commodities. We study jointly the global returns to value and momentum and explore their common factor structure. We find that value (momentum) in one asset class is positively correlated with value (momentum) in other asset classes, and value and momentum are negatively correlated within and across asset classes. Liquidity risk is positively related to value and negatively to momentum, and its importance increases over time, particularly following the liquidity crisis of 1998. These patterns emerge from the power of examining value and momentum everywhere simultaneously and are not easily detectable when examining each asset class in isolation.

Figure 1: Performance of value and momentum strategies

Plotted are the cumulative returns to value, momentum, and a 50/50 combination of value and momentum strategies among individual stocks in four markets: U.S., U.K., Japan, and Continental Europe, in four different asset classes: Country equity index futures, country bonds, currencies, and commodities, and for the equal-weighted combination of all stock selection strategies, all non-stock selection strategies, and an equal-weighted combination of both. Also reported on each figure are the annualized Sharpe ratios of each strategy and the correlation between value and momentum in each market.

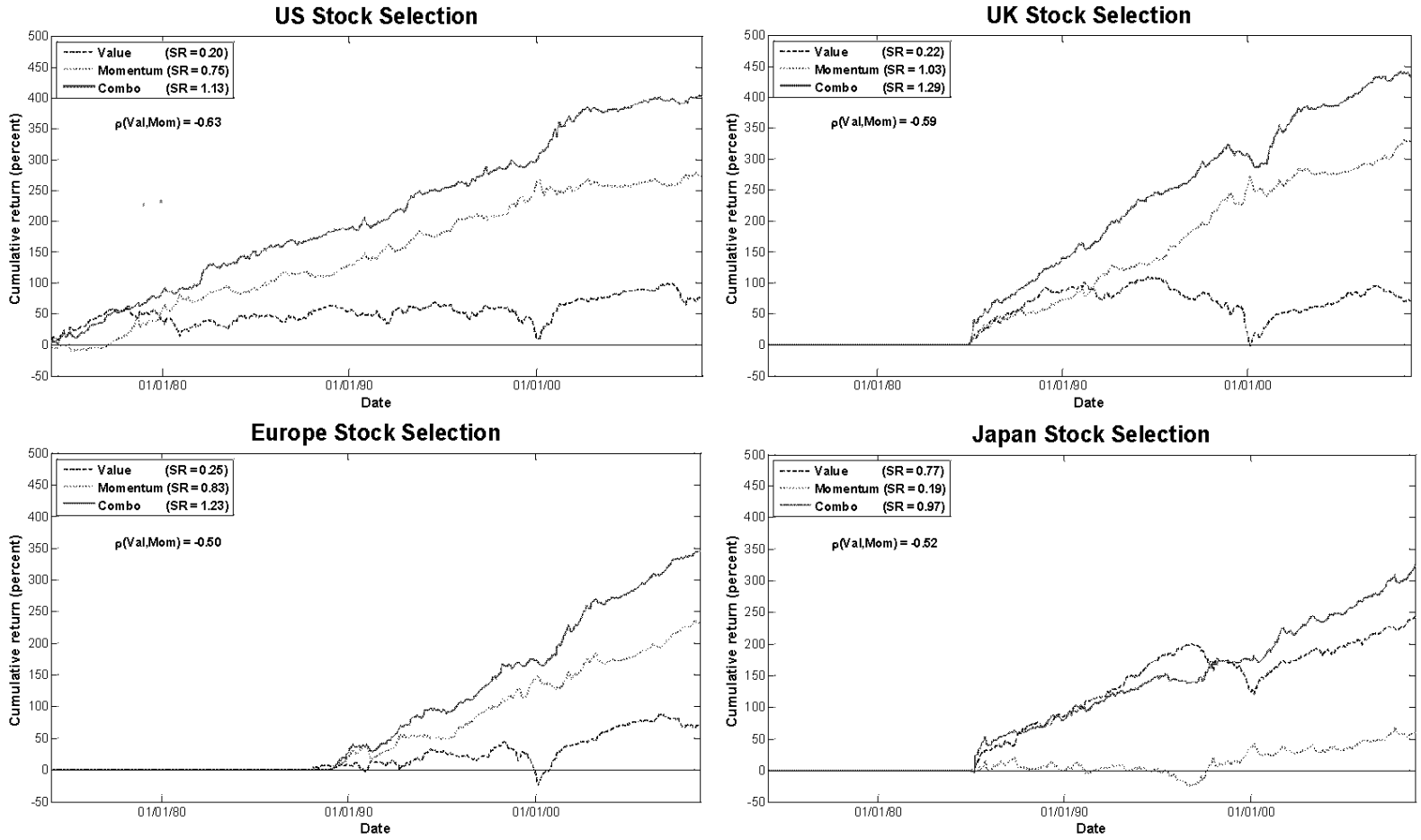


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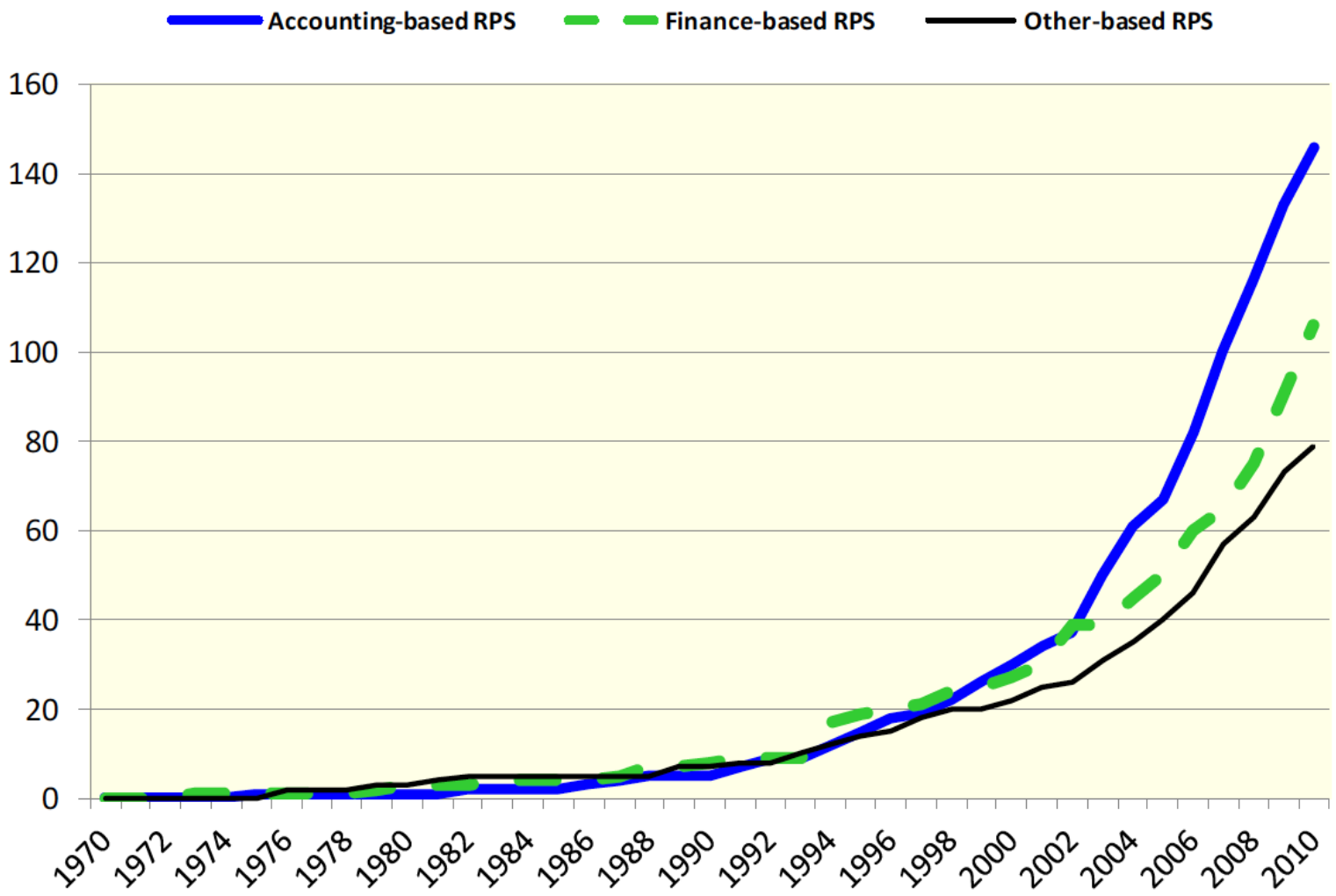
FIGURE 1 (Green, Hand, Zhang, 2014)

The cumulative number of return predictive signals (RPS) discovered and publicly reported by accounting, finance and other business academics, 1970-2010.



More anomalies (Green, Hand, Zhang, 2014)

TABLE 6

Key descriptors of the set of 39 readily programmed RPS from our RPS population database. Each RPS is implemented in such a way that it generates a positive expected mean long/short hedge return. Mean returns and the standard deviation of monthly returns are annualized by multiplying monthly returns by 12 and the standard deviation of monthly returns by sqrt(12).

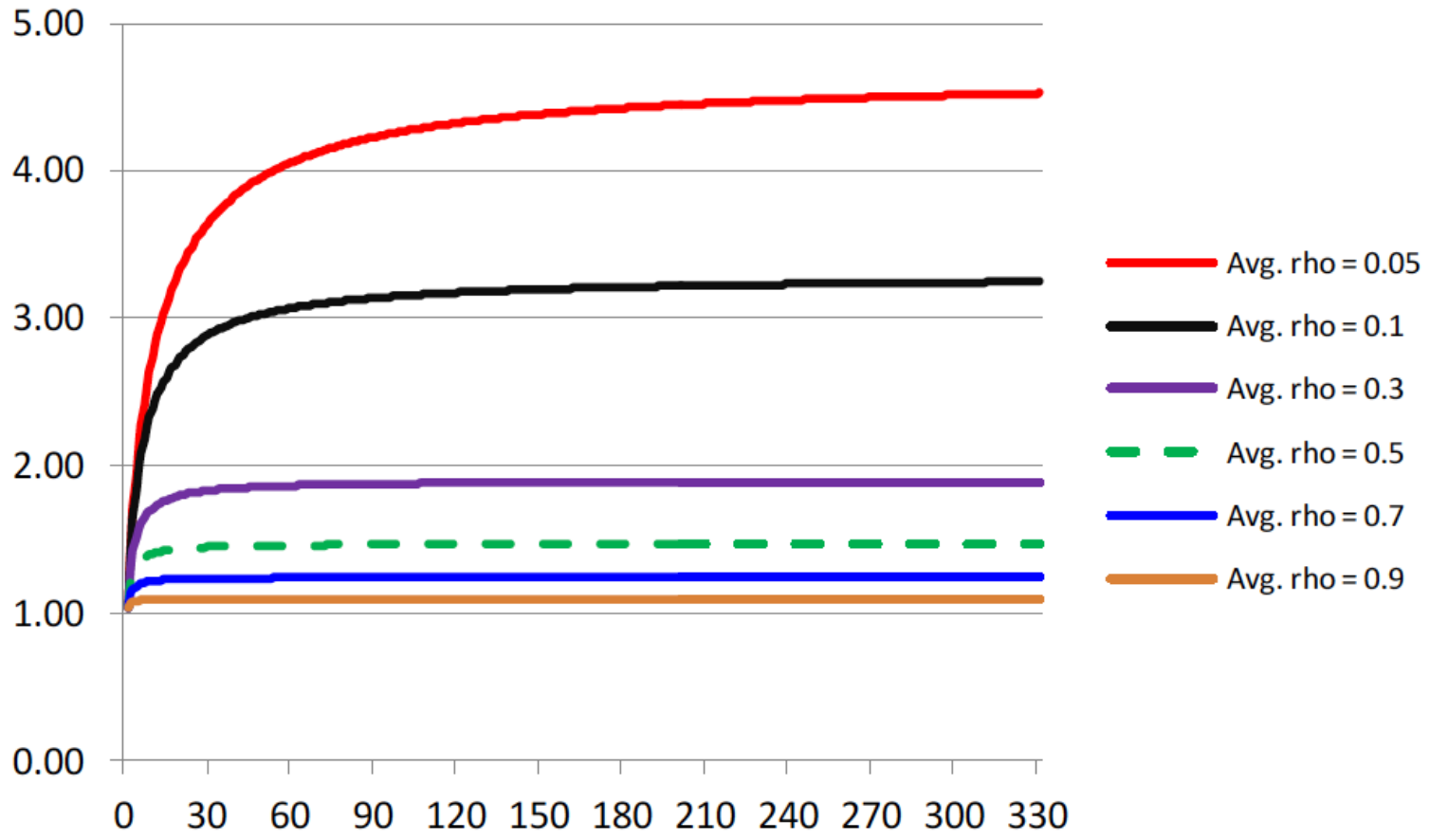
				Equal-weighted returns			*Value-weighted returns*		
#	**Author(s)**	**Date, Journal**	**Signal**	**Mean Return**	**Std. Dev.**	**Sharpe ratio**	**Mean Return**	**Std. Dev.**	**Sharpe ratio**
	--	--	Risk-free rate (1 month treasury bill)	4.0%	0.7%		4.0%	0.7%	
	--	--	Market less risk-free rate	8.8%	19.1%	0.46	7.1%	16.1%	0.44
1	Banz	1981, JFE	Firm size	13.8%	20.1%	0.69	0.4%	19.6%	0.02
2	Rosenberg, Reid & Lanstein	1985, JPM	Book-to-market	14.6%	13.9%	1.05	5.6%	17.9%	0.32
3	Jegadeesh	1990, JF	12 month momentum	-3.6%	33.4%	-0.11	18.0%	34.2%	0.53
4	Jegadeesh & Titman	1993, JF	One month momentum	27.5%	26.6%	1.03	2.5%	25.5%	0.10
5	Gettleman & Marks	2006, WP	Change in 6 month momentum	9.6%	17.9%	0.54	6.5%	21.3%	0.31
6	Cooper, Gulen & Schill	2008, JF	Asset growth	22.2%	14.7%	1.51	8.9%	15.5%	0.57
7	Basu	1977, JF	Earnings-to-price	-4.7%	22.9%	-0.20	2.4%	22.9%	0.11
8	Sloan, R.G.	1996, TAR	Working capital accruals	6.8%	7.2%	0.94	4.7%	11.7%	0.40
9	Hafzalla, Lundholm & Van Winkle	2011, TAR	Percent accruals	2.7%	14.3%	0.19	-1.4%	15.3%	-0.09
10	Chemmanur & Yan	2009, WP	Change in advertising expense	-0.4%	14.4%	-0.03	8.8%	14.2%	0.62
11	Chen & Zhang	2010, JF	Capital expenditures and inventory	18.2%	11.7%	1.55	6.6%	11.7%	0.57
12	Pontiff & Woodgate	2008, JF	Change in shares outstanding	12.6%	12.1%	1.03	7.0%	11.1%	0.63

				Equal-weighted returns			*Value-weighted returns*		
#	**Author(s)**	**Date, Journal**	**Signal**	**Mean Return**	**Std. Dev.**	**Sharpe ratio**	**Mean Return**	**Std. Dev.**	**Sharpe ratio**
13	Richardson, Sloan, Soliman & Tuna	2005, JAE	Change in long-term debt	12.3%	8.4%	1.46	5.2%	11.8%	0.44
14	Richardson, Sloan, Soliman & Tuna	2005, JAE	Change in common shareholder equity	11.5%	12.0%	0.96	5.8%	11.8%	0.49
15	Soliman	2008, TAR	Industry-adjusted change in profit margin	0.2%	8.6%	0.03	2.9%	11.7%	0.25
16	Soliman	2008, TAR	Industry-adjusted change in asset turnover	4.6%	5.5%	0.84	4.4%	9.6%	0.45
17	Thomas & Zhang	2011, TAR	Change in tax expense	13.3%	8.0%	1.66	6.5%	12.5%	0.52
18	Rendleman, Jones & Latané	1982, JFE	Unexpected quarterly earnings	20.4%	8.9%	2.28	11.8%	15.4%	0.77
19	Brandt, Kishore, Santa-Clara & Venkatachalam	2009, WP	3-day return around earnings announcement	12.8%	8.6%	1.49	6.7%	11.6%	0.58
20	Chandrashekar & Rao	2009, WP	Cash-to-price	7.8%	10.5%	0.74	4.3%	11.1%	0.38
21	Hou & Robinson	2006, JF	Industry sales concentration	4.0%	12.3%	0.33	-0.3%	12.8%	-0.03
22	Balakrishnan, Bartov & Faurel	2010, JAE	ROA	11.1%	23.4%	0.47	8.5%	22.5%	0.38
23	Novy-Marx	2012, WP	Gross profitability	0.4%	13.5%	0.03	5.9%	14.9%	0.39
24	Lerman, Livnat & Mendenhall	WP	Abnormal volume in earnings announcement month	6.6%	7.1%	0.93	3.8%	12.4%	0.30
25	Chordia, Subrahmanyam, & Anshuman	JFE, 2001	Dollar trading volume from month t-2	13.3%	18.2%	0.73	-0.2%	12.1%	-0.01
26	Bali, Cakici & Whitelaw	2011, JFE	Maximum daily return in prior month	0.4%	29.4%	0.02	10.0%	30.5%	0.33

				Equal-weighted returns			*Value-weighted returns*		
#	**Author(s)**	**Date, Journal**	**Signal**	**Mean Return**	**Std. Dev.**	**Sharpe ratio**	**Mean Return**	**Std. Dev.**	**Sharpe ratio**
27	Lamont & Frazzini	WP	Earnings announcement month	4.8%	5.9%	0.81	6.6%	6.5%	1.03
28	Diether, Malloy & Scherbina	2002, JF	Dispersion in forecasted EPS	12.4%	15.7%	0.79	8.5%	19.8%	0.43
29	Hawkins, Chamberlain & Daniel	1984, FAJ	Change in forecasted EPS	12.9%	9.6%	1.35	5.1%	12.9%	0.40
30	Bauman & Dowen	1988, FAJ	Forecasted growth in 5-year EPS	3.6%	27.9%	0.13	0.4%	29.9%	0.01
31	Bandyopadhyay, Huang, & Wirjanto	2010, WP	Accrual volatility	4.3%	22.3%	0.19	5.4%	18.3%	0.29
32	Brown & Rowe	2007, WP	Return on invested capital	-0.1%	22.1%	0.00	10.8%	23.5%	0.46
33	Eberhart, Maxwell, & Siddique	2004,JF	R&D increase	4.5%	18.3%	0.25	0.2%	11.9%	0.01
34	Huang	2009, JEF	Cash flow volatility	3.0%	22.2%	0.14	8.5%	18.6%	0.46
35	Thomas & Zhang	2002, RAS	Changes in inventory	13.7%	8.2%	1.67	6.0%	12.1%	0.49
36	Ang, Hodrick, Xing, & Zhang	2006,JF	Return volatility	-3.6%	33.1%	-0.11	17.3%	36.0%	0.48
37	Asness, Porter, & Stevens	WP	Industry adjusted change in employees	12.0%	8.6%	1.39	5.9%	11.2%	0.53
38	Bazdresch, Belo, & Lin	2010, WP	Employee growth rate	16.1%	12.3%	1.31	4.9%	13.3%	0.37
39	Datar, Naik, & Radcliffe	1998, JFM	Turnover	30.0%	27.8%	1.08	4.0%	24.1%	0.17
			Mean across N = 39 RPS	9.0%	15.8%	0.75	5.9%	16.9%	0.37

Construct a scoring model based on signals

Panel A: Portfolio Sharpe ratios as a function of the number of RPS in the portfolio, for varying levels of average cross-correlations between RPS returns



Example: SCORE BASED ON SEVERAL RPS
Other information to support discretionary decision making

NAME	SCORE	PRICE	% to Target Price	P/E	P/B	Analyst recommendation
DRAGON OIL	84.5	7.2	0.44	8.0	1.39	4.75
KING DIGITAL ENT	81.4	19.3	0.30	8.1	33.69	4.71
FORD MOTOR CO	81.3	17.1	0.17	12.9	2.48	4.23
WESTJET AIRLINES	78.6	28.9	0.17	12.6	2.22	4.50
TYSON FOODS-A	78	36.9	0.26	13.1	1.94	4.20
ALLIANCE RESOURC	77.4	47.0	0.14	10.2	3.66	3.89
CIGNA CORP	76.9	90.6	0.09	12.3	2.19	3.96
AFLAC INC	76.9	59.2	0.16	9.5	1.53	3.52
HERBALIFE LTD	76.1	51.5	0.59	8.2		4.43
FLEXTRONICS INTL	75.8	10.6	0.19	10.6	2.75	3.53
WEST FRASER TIMB	75.5	47.3	0.33	12.4	2.02	4.50
GKN PLC	75.5	342.4	0.20	12.3	3.33	4.20
CISCO SYSTEMS	75.1	25.0	0.06	12.3	2.30	3.94
DELPHI AUTOMOTIV	75	68.5	0.22	13.4	6.60	4.38
AXA	74.6	17.6	0.22	8.4	0.81	4.41
UNIQA INSURANCE	74.6	9.0	0.21	9.3	0.95	3.70
EASYJET PLC	74.5	1228.0	0.39	10.9	2.93	4.12
FREENET AG	74.4	18.4	0.26	9.9	2.02	4.00
CDW CORP/DE	74.3	30.9	0.14	13.5	6.28	4.45
BP PLC	74.3	464.0	0.14	9.7	1.09	3.72
PIRELLI & C.	74.2	11.0	0.20	12.3	2.19	3.63
BOMBARDIER INC-B	74.2	3.8	0.19	9.1	2.58	3.40
BELLWAY PLC	74.1	1475.0	0.25	9.9	1.41	4.41
VERIZON COMMUNIC	74	48.7	0.13	13.7	13.55	4.23
MACY'S INC	73.9	60.2	0.07	13.4	3.56	4.50
MARINE HARVEST	73.9	76.2	0.26	9.4	1.91	4.29
AETNA INC	73.9	76.7	0.16	11.7	1.85	4.22
MICRON TECH	73.9	30.0	0.33	9.6	3.16	4.22
LEAR CORP	73.8	95.4	0.14	12.0	2.43	4.31
NCR CORP	73.7	30.5	0.28	10.2	2.64	3.30
PETROFAC LTD	73.6	1076.0	0.28	10.3	3.14	4.04
DELTA AIR LI	73.5	36.2	0.37	11.2	2.50	4.95

Macroeconomic variables and equity market

There exists some evidence that also macroeconomic factors, such as industrial production, affect stock market expected returns.

In addition, there is evidence that momentum is present internationally.

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Learning as a market correcting force

R. David McLean and Jeffrey Pontiff (2013) study the out-of-sample and post-publication return-predictability of 82 characteristics that are identified in published academic studies. The average out-of-sample decay due to statistical bias is about 10%, but not statistically different from zero. The average post-publication decay, which we attribute to both statistical bias and price pressure from aware investors, is about 35%, and statistically different from both 0% and 100%. Our findings point to mispricing as the source of predictability. Post-publication, stocks in characteristic portfolios experience higher volume, variance, and short interest, and higher correlations with portfolios that are based on published characteristics. Consistent with costly (limited) arbitrage, post-publication return declines are greater for characteristic portfolios that consist of stocks with low idiosyncratic risk.

-After academics publish an anomaly, the anomaly is decreased by 35%.

-Trading related to anomaly increases.

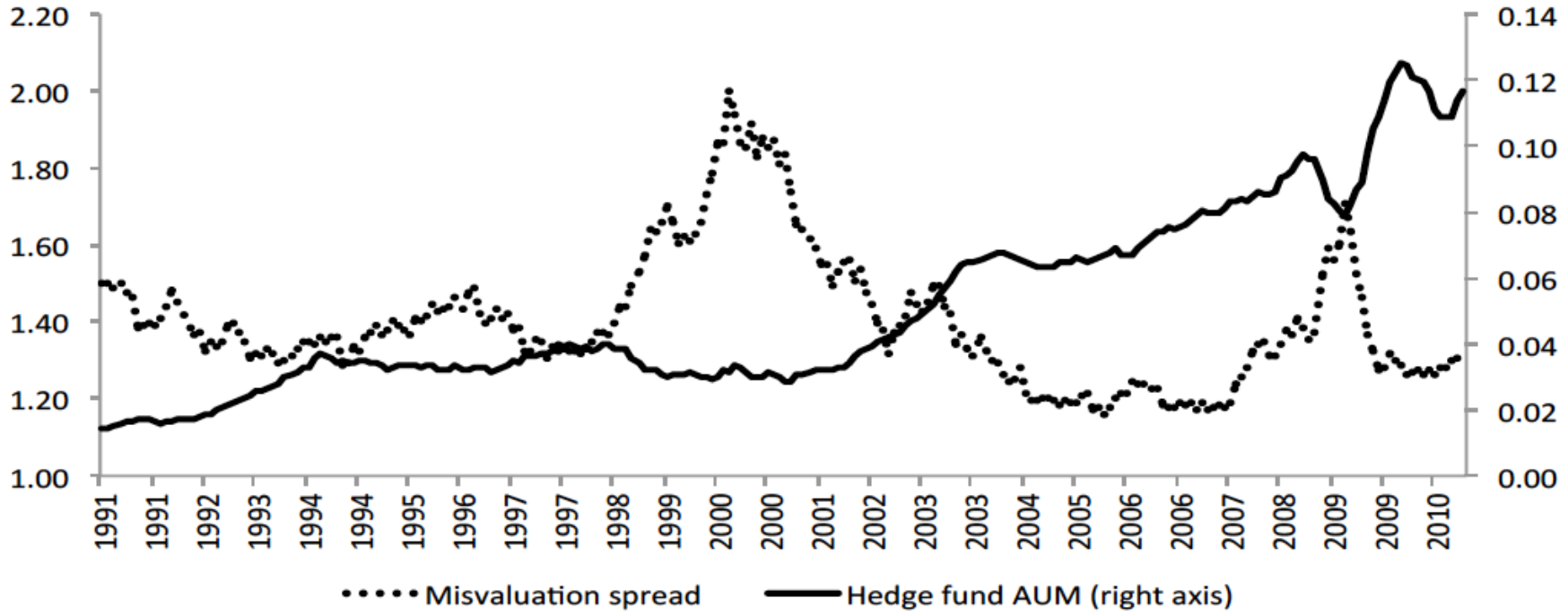
Hedge Funds as a Market Correcting Force

- Kokkonen Suominen find that hedge funds trade to improve market efficiency.

- Buy more undervalued than overvalued shares
  - Especially at times when misvaluation spread is large.
  - When hedge fund capital increases or leverage opportunities improve.

Figure 1
Misvaluation Spread and Hedge Fund AUM

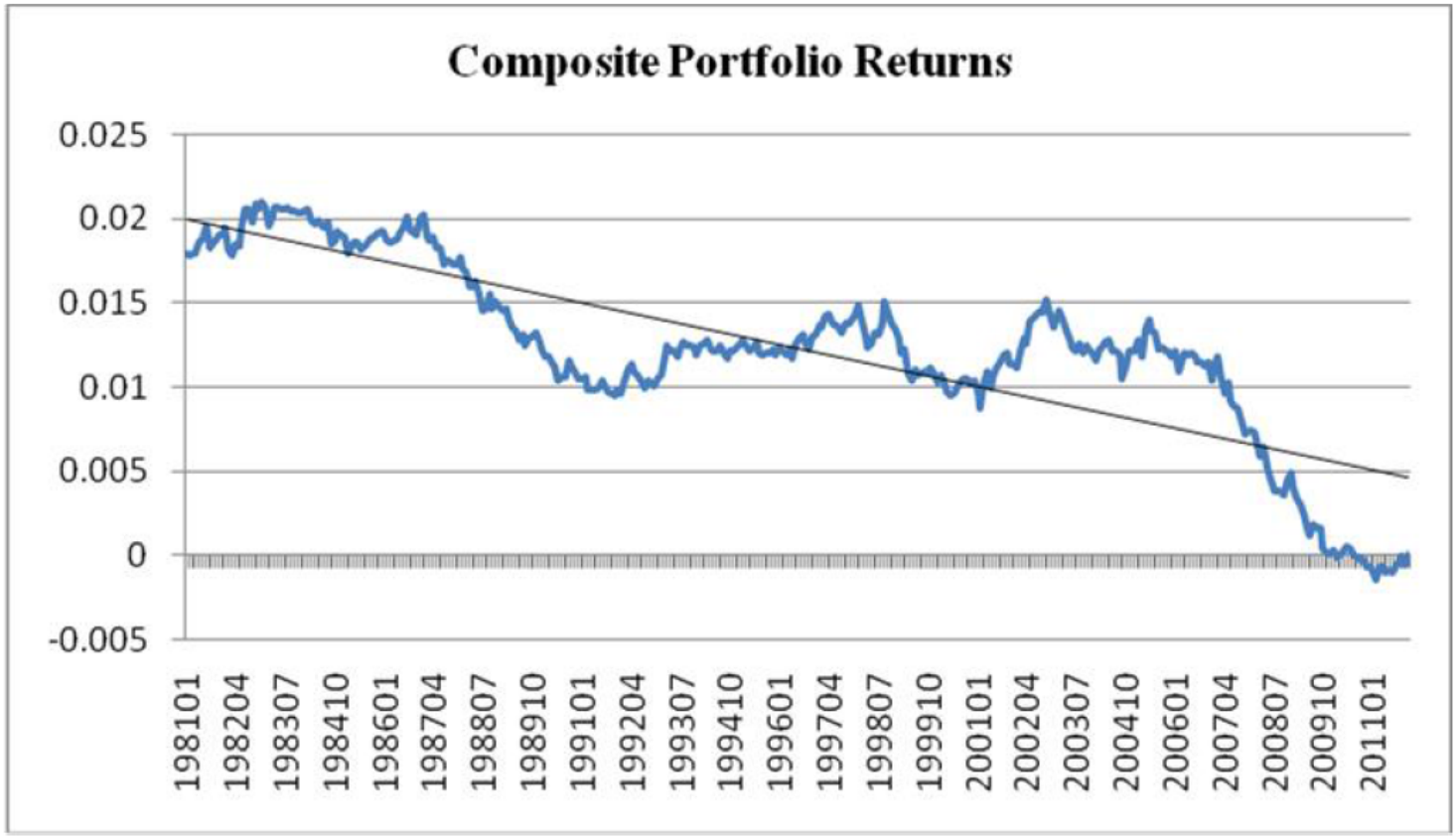
This figure plots the misvaluation spread (our measure of market level misvaluation) together with the hedge fund AUM. The AUM has been scaled by the average CRSP stock market capitalization of the previous 12 months. The misvaluation spread is defined as the difference in the misvaluations of the highest three deciles of stocks and the lowest three deciles of stocks ranked by their misvaluations. The decile breakpoints are calculated using NYSE stocks only. The misvaluation spread corresponds with the difference in the misvaluations of the Overvalued and the Undervalued portfolios defined in the text and in Table 1.



Chordia Subra, Tong 2014, find that returns to anomalies based trading strategy have declined over time

Figure 2: Trend in the Returns to a Composite Anomalies-Based Portfolio

This figure shows the five-year moving averages of the returns of the composite portfolio for NYAM stocks, based on all twelve anomalies that we consider. The composite portfolio returns are computed using the method of Lehmann (1990), where the weights are based on averaging percentile rank scores of various characteristics for each stock on portfolios.



Part II

- Momentum factor
- Value Factor
- Other anomalies
- Market correcting forces
- Summary

Conclusions

- Momentum is strong. Possibly related to spreading of information.
- Value phenomenon is also strong and possibly related to mispricing
- Market correcting forces have decreased predictability
  - Hedge fund capital
  - Academic research