Lecture 5: Momentum

1. Jegadeesh and Titman (1993) – Momentum effect.
2. Moskowitz and Grinblatt (1999) on momentum and industry effects.
   - Also related papers on momentum: Grundy and Martin (2000), Hong, Lim, and Stein (2000), Jegadeesh and Titman (2001).
3. Grinblatt and Moskowitz (2004) synthesis view of momentum.
4. Lee and Swaminathan (2001) and Hvidkjaer (2005) on trading activity and momentum.
5. Daniel and Moskowitz (2013) on momentum "crashes."
6. Behavioral factors: the disposition effect; Frazzini (2006).

Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency
– Jegadeesh and Titman (1993,JF)

Momentum is the fact that stocks that have performed *relatively* well in the past continue to perform *relatively* well in the future, and stocks that have performed relatively poorly, continue to perform relatively poorly.

A **Momentum investment or "relative strength" strategy** buys stocks which have performed relatively well in the past and sells (shorts) stocks which have performed relatively poorly.

Over the 1963-1990 time period, Jegadeesh and Titman (1993) found that a strategy that ranked stocks based on their past 6 months to a year returns, and bought the top 10% and shorted the bottom 10% based on this ranking, produced abnormal returns of 12% per year.

Why is momentum interesting?

- Seems to violate even the weakest form of efficient markets.
- magnitude: generates a 12% abnormal return on a zero-investment strategy.

– these strategies are typically beta neutral.
– they are also not affected by the FF factors.
  i.e., momentum remains the biggest puzzle to the FF 3-factor model.

- puzzling horizon at which momentum is profitable:

Past Return Predictability in General:

1. Long-term reversals
   - DeBondt and Thaler (1985)
   - 3-5 year contrarian strategy
2. Short-term (< 1 month) reversals
   - Jegadeesh (1990), Lehman (1990), Lo and MacKinlay (1988)
3. Intermediate horizon continuation
   - Jegadeesh and Titman (1993)
   - 3-12 month momentum strategy
   - profits dissipate over 1-year and start to reverse after 2-3 years → temporary price effect.
   - see similar pattern around earnings announcements (both earnings and price momentum).

What could be driving momentum?

1. Systematic risk? (covariance or consumption state variables)
2. Delayed stock price reactions to common factors (lead-lag effect)?
3. Microstructure effects?
4. Survivorship or selection bias?
5. Data mining?
6. Underreaction? (JT claim delayed price reaction to *firm-specific* news)
7. Delayed overreaction?

Simple decomposition of the potential sources of momentum profits:

Momentum implies that stocks that outperformed the average stock in the past, will outperform the average stock in the future. where $\overline{r}_t = \frac{1}{N} \sum_{j=1}^{N} \tilde{r}_{jt}$

$$\begin{aligned} E[\tilde{r}_{jt} - \overline{r}_t | \tilde{r}_{jt-1} - \overline{r}_{t-1} > 0] &> 0 \\ E[\tilde{r}_{jt} - \overline{r}_t | \tilde{r}_{jt-1} - \overline{r}_{t-1} < 0] &< 0 \\ \Rightarrow E[(\tilde{r}_{jt} - \overline{r}_t)(\tilde{r}_{jt-1} - \overline{r}_{t-1})] &> 0 \end{aligned}$$

where $\overline{r}_t$ is the cross-sectional or equal-weighted average return of stocks at time t (a bar over a variable represents its cross-sectional average in this section). This equation represents the expected payoff to a self-financing momentum investment strategy where $(\tilde{r}_{jt-1} - \overline{r}_{t-1})$ is the amount invested in stock j at time t, funded by shorting the same amount in the equal-weighted portfolio. Momentum in stock returns implies that this expression is positive.

Assume a 1-Factor model, and t is a 6-month period,

$$\tilde{r}_{jt} = \mu_j + \beta_j \tilde{F}_{1t} + \tilde{\epsilon}_{jt}$$

$$\begin{aligned}
&E[(\tilde{r}_{jt} - \overline{r}_t)(\tilde{r}_{jt-1} - \overline{r}_{t-1})] = \\
&E[([\mu_j + \beta_j \tilde{F}_{1t} + \tilde{\epsilon}_{jt}] - [\overline{\mu} + \overline{\beta}\tilde{F}_{1t}])([\mu_j + \beta_j \tilde{F}_{1t-1} + \tilde{\epsilon}_{jt-1}] - [\overline{\mu} + \overline{\beta}\tilde{F}_{1t-1}])] = \\
&(\mu_j - \overline{\mu})^2 + (\beta_j - \overline{\beta})^2 cov(\tilde{F}_{1t}, \tilde{F}_{1t-1}) + cov(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1})
\end{aligned}$$

Averaging over all N stocks, momentum trading profits equal,

$$\begin{aligned}
&= \frac{1}{N}\sum_{j=1}^{N}[(\mu_j - \overline{\mu})^2 + (\beta_j - \overline{\beta})^2 cov(\tilde{F}_{1t}, \tilde{F}_{1t-1}) + cov(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1})] \\
&= \sigma_\mu^2 + \sigma_\beta^2 cov(\tilde{F}_{1t}, \tilde{F}_{1t-1}) + \frac{1}{N}\sum_{j=1}^{N} cov(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1})
\end{aligned}$$

Possible Sources:

1. σ_μ^2 – cross-sectional variation in mean returns.
   - Not related to market β, size, or even BE/ME.
2. $\sigma_\beta^2 cov(\tilde{F}_{1t}, \tilde{F}_{1t-1})$ – serial covariation in the factor returns.

- "timing" the factor.
- $cov(R_{mt}, R_{mt-1}) = \overline{\beta}^2 Cov(\tilde{F}_{1t}, \tilde{F}_{1t-1}) < 0.$

3. $Cov(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1})$–Jegadeesh and Titman (1993) claim this last term is the source.

   But, $Cov(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1}) > 0$ could be driven by lead-lag effect resulting from delayed reaction to macro shocks.

   Consider, a 1-Factor model with a delayed reaction for some stocks,

$$\tilde{r}_{jt} = \mu_j + \beta_{1j}\tilde{F}_{1t} + \beta_{2j}\tilde{F}_{1t-1} + \tilde{\epsilon}_{jt}$$

4. Skipping a week mitigates the lead-lag effect, yet profits on momentum are larger.

5. No evidence that a delayed effect drives momentum profitability.

   - but, ϵ's are diversifiable, therefore, ...
     arbitrage opportunity?
   - So, why doesn't it go away?
   - Investors tend to underreact to firm-specific information (i.e., they are consistently irrational).
   - But, all you need is *some* rational investors who are willing to arbitrage this away.

6. What if ϵ contains other factors?

Do Industries Explain Momentum? – Moskowitz and Grinblatt (1999, JF)

- claim industry effects drive most of momentum profits.
- Separate ϵ into industry and residual component:

$$\epsilon_{jt} = \delta_{mt} + \epsilon^*_{jt}$$

They consider a more general framework allowing for time-variation in expected returns (μ_t) and factor loadings, as well as multiple factors ($\sum_{k=1}^{K} \beta_{k,t}\tilde{F}_{kt}$).

- $Cov(\mu_{jt}, \mu_{jt-1})$ (time-varying expected returns) does not explain it.
- $Cov(\tilde{F}_t, \tilde{F}_{t-1})$ (momentum in factors) or $Cov(\beta_{jt}, \beta_{jt-1})$ cannot explain it.
  - $Cov(\tilde{F}_t, \tilde{F}_{t-1}) < 0$ (even for FF factors), suggesting this is not the likely source of profits.
  - $Cov(\beta_{jt}, \beta_{jt-1})$ goes in the wrong direction as shown by Grundy and Martin (2000).
- Moskowitz and Grinblatt (1999) argue $Cov(\delta_{mt}, \delta_{mt-1}) > 0$, but $Cov(\epsilon^*_{mt}, \epsilon^*_{mt-1}) \approx 0$.
- Grundy and Martin (2000) argue $Cov(\delta_{mt}, \delta_{mt-1}) > 0$, *and* $Cov(\epsilon^*_{mt}, \epsilon^*_{mt-1}) > 0$.
- Conrad and Kaul (1998) argue $Cov(\mu_{jt}, \mu_{jt-1})$ explains it, but both Moskowitz and Grinblatt (1999) and Grundy and Martin (2000) disagree.

Table 1: Momentum Profits for Individual Equities, Industries, and Random Industries

		Panel A: Individual Stock Momentum					
(L,H)		Raw		DGTW		Size and BE/ME	
		$\tilde{r}_{jt}$		$\tilde{r}^{*}_{jt}$		$\tilde{r}^{sb}_{jt}$	
		Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
(6,6)	Wi-Lo	0.0043	(4.65**)	0.0009	(1.56)	0.0029	(3.34**)
		Raw − Industry		Size, BE/ME, and Industry		Size, BE/ME, and Random[a] Industry	
		$\tilde{r}_{jt} - \tilde{R}_{It}$		$\tilde{r}^{sb,I}_{jt}$		$\tilde{r}^{sb,\spadesuit}_{jt}$	
		Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
(6,6)	Wi-Lo	0.0013	(2.04*)	0.0008	(0.91)	0.0027	(2.77**)

		Panel B: Industry and Random Industry Momentum					
(L,H)		Raw Industry		DGTW Industry		Raw Random[a]	
		$\tilde{R}_{It}$		$\tilde{R}^{*}_{It}$		Industry, $\tilde{R}^{\spadesuit}_{It}$	
		Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
(6,6)	Wi-Lo	0.0043	(4.24**)	0.0020	(2.27*)	-0.0005	(-1.09)

		Panel C: Individual Stocks, Raw Returns					
(L,H)		Industry Neutral		Excess Industry		High Ind. Losers − Low Ind. Winners	
		$\tilde{r}_{jt}$		$\tilde{r}_{jt}$		$\tilde{r}_{jt}$	
		Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
(6,6)	Wi-Lo	0.0011	(1.01)	-0.0007	(-0.83)	0.0030	(2.66**)

[a] Random industries are generated by replacing each stock return with an equal-weighted average of the stocks ranked above and below it based on their past 6-month returns.

*Significant at the 5% level. **Significant at the 1% level.

Source: Moskowitz and Grinblatt, 1999, *Journal of Finance*.

Another decomposition of momentum profits.

Momentum has both a time-series and cross-sectional component. (We will explore the cross-sectional component here, but later will look at evidence for the time-series component.) We can decompose momentum profits into these two pieces to see which is more important empirically. This may then help us in identifying momentum's source of returns and what explanation fits the data best.

Let $w_{i,t} = \frac{1}{N}(r_{i,t-1} - \overline{r}_{t-1})$

Momentum profits at time t equal $\pi_t = \sum_{i=1}^{N} w_{i,t}\tilde{r}_{i,t}$

$$\begin{aligned}
E[\pi_t] &= \frac{1}{N}E[\sum_{i=1}^{N} r_{i,t-1}\tilde{r}_{i,t}] - \frac{1}{N}E[\sum_{i=1}^{N} \overline{r}_{t-1}\tilde{r}_{i,t}] \\
&= \frac{1}{N}E[\sum_{i=1}^{N} r_{i,t-1}\tilde{r}_{i,t}] - \frac{1}{N}E[\overline{r}_{t-1}\sum_{i=1}^{N} \tilde{r}_{i,t}] \\
&= \frac{1}{N}\sum_{i=1}^{N} E[r_{i,t-1}\tilde{r}_{i,t}] \\
&= \frac{1}{N}\sum_{i=1}^{N}[cov(r_{i,t-1}, \tilde{r}_{i,t}) + \mu_i^2] - E[\overline{r}_{t-1}\frac{1}{N}\sum_{i=1}^{N} \tilde{r}_{i,t}] \\
&= \frac{1}{N}\sum_{i=1}^{N}[cov(r_{i,t-1}, \tilde{r}_{i,t}) + \mu_i^2] - [cov(\overline{r}_{t-1}, \overline{r}_t) + \overline{\mu}^2)] \\
&= \frac{1}{N}\sum_{i=1}^{N}(\rho_i + \mu_i^2) - (\rho_m + \mu_m^2)
\end{aligned}$$

$$= \frac{1}{N}\sum_{i=1}^{N}\rho_i - \rho_m + \frac{1}{N}\sum_{i=1}^{N}\mu_i^2 - \mu_m^2$$

Define $\Omega = E[r_{t-1} - \mu)(r_t - \mu)']$

$$\begin{aligned} E[\pi_t] &= \frac{tr(\Omega)}{N} - \frac{1'\Omega 1}{N^2} + \sigma_\mu^2 \\ &= \frac{N-1}{N}tr(\Omega) - \frac{1}{N^2}[1'\Omega 1 - tr(\Omega)] + \sigma_\mu^2 \end{aligned}$$

= diagonals − off diagonals + cross-sectional variation in means

= autocovariances + cross-serial covariances + dispersion in mean returns

Momentum Definition

Momentum is the phenomenon that stocks which have performed well in the past *relative* to other stocks (winners) continue to perform well in the future, and stocks that have performed *relatively* poorly (losers) continue to perform poorly.

A ***momentum investment strategy*** buys stocks which have performed relatively well in the past and sells (or shorts) stocks which have performed relatively poorly.

Outline

- Historical Evidence
- Past return predictability over horizons
- Explanations: behavioral vs. risk-based vs. data mining
- Sources and refinements
- Risks
- Other types of momentum
- Conclusion

Simple Momentum Strategy

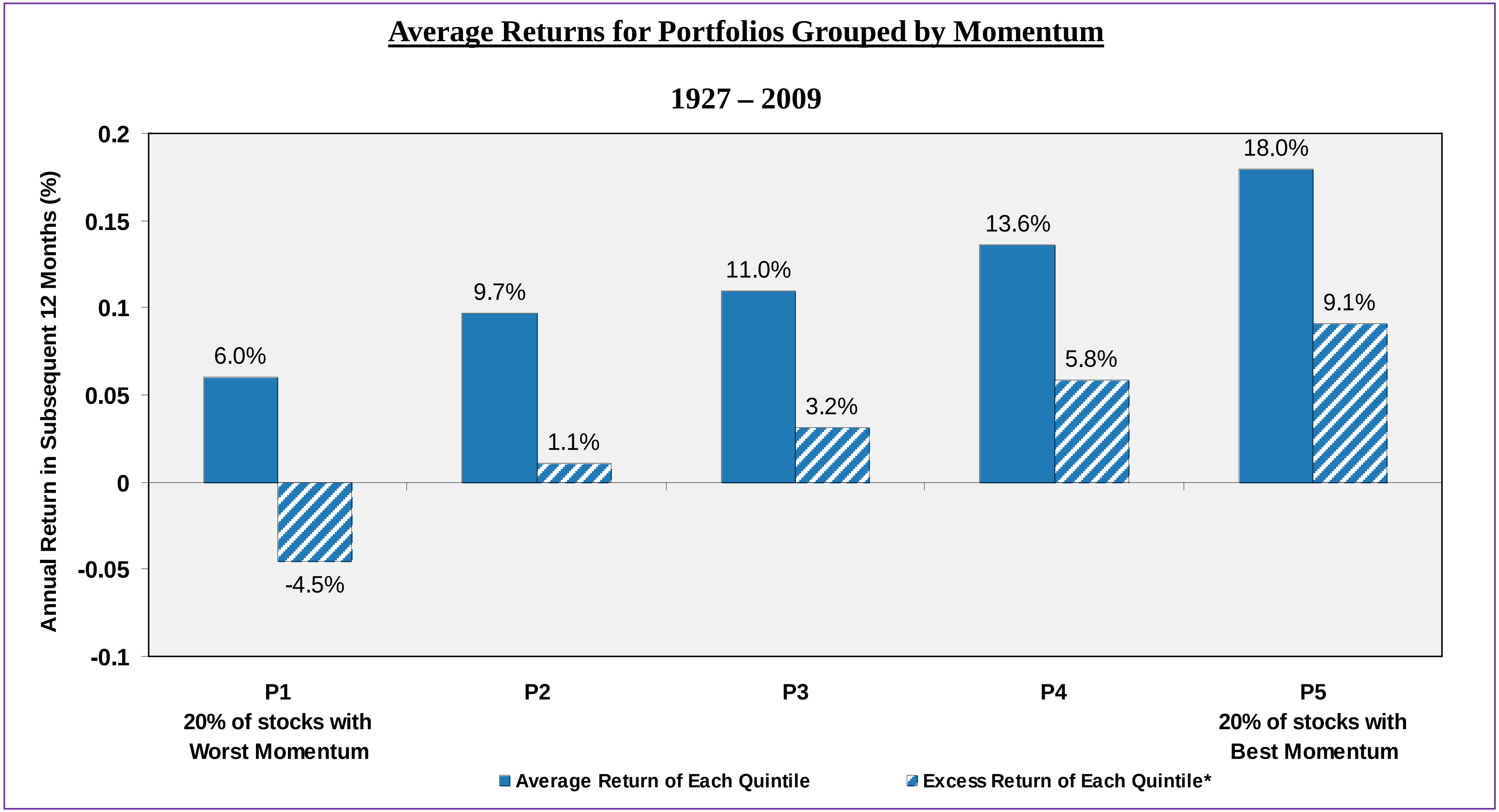
- Rank stocks on past 6-12 month raw returns
- Form deciles (equal or value weight)
- Measure return over next month

- More power: use rolling 6-month windows and hold positions for 6 months
- Measured return in any month is average of six strategies ranked on returns from: t-1 to t-6, t-2 to t-7, …, t-6 to t-11
- Only update 1/6 of the weights each month, which lowers turnover considerably

Average Monthly Returns for Portfolios Grouped by Momentum (6-month rank, 6-month hold) (1965 - 2008)

Momentum Ranked Decile Portfolio	Average Monthly Return (%)	
P1 (losers)	0.46	
P2	0.09	
P3	1.05	
P4	1.12	
P5	1.15	
P6	1.18	
P7	1.21	
P8	1.30	
P9	1.41	
P10 (winners)	1.63	
Decile 10 - 5 (winners)	0.48	41.03%
Decile 5 - 1 (losers)	0.69	58.97%
Decile 10 - 1 (winners - losers)	**1.17**	***4.96***

Historical Evidence



* Source: CRSP Database. Data is based on monthly returns from overlapping portfolios. Momentum is calculated by ranking stocks based on their past 12-month return excluding the most recent month. Returns are in excess of the beta-adjusted CRSP Value Weighted Index. Past performance is not an indication of future performance.

Fama-French Regressions (1927-2012)

$$R_{it} - r_{ft} = \alpha_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

	alpha	*t*(alpha)	b	s	h	R-square
P1 (losers)	-0.67	-3.43	1.29	0.51	0.38	0.77
P2	-0.32	-2.47	1.23	0.14	0.38	0.85
P3	-0.22	-2.36	1.11	-0.01	0.33	0.89
P4	-0.12	-1.53	1.08	-0.04	0.26	0.92
P5	-0.07	-1.12	1.04	-0.06	0.23	0.93
P6	0.10	1.84	0.99	-0.05	0.16	0.94
P7	0.19	3.54	0.97	-0.11	0.08	0.94
P8	0.33	5.03	0.95	-0.09	0.02	0.92
P9	0.52	6.86	0.95	-0.04	-0.04	0.89
P10 (winners)	0.87	8.00	0.99	0.25	-0.29	0.82
P10-P1	**1.53**	**5.93**	**-0.30**	**-0.25**	**-0.68**	**0.23**

Risk Adjustment

Factor exposure

– Buying winners and shorting losers guarantees time-varying factor exposure.

– Factor models can explain 80-90% of momentum variation, but cannot explain their mean returns.

– Alpha is remarkably stable over the last century.

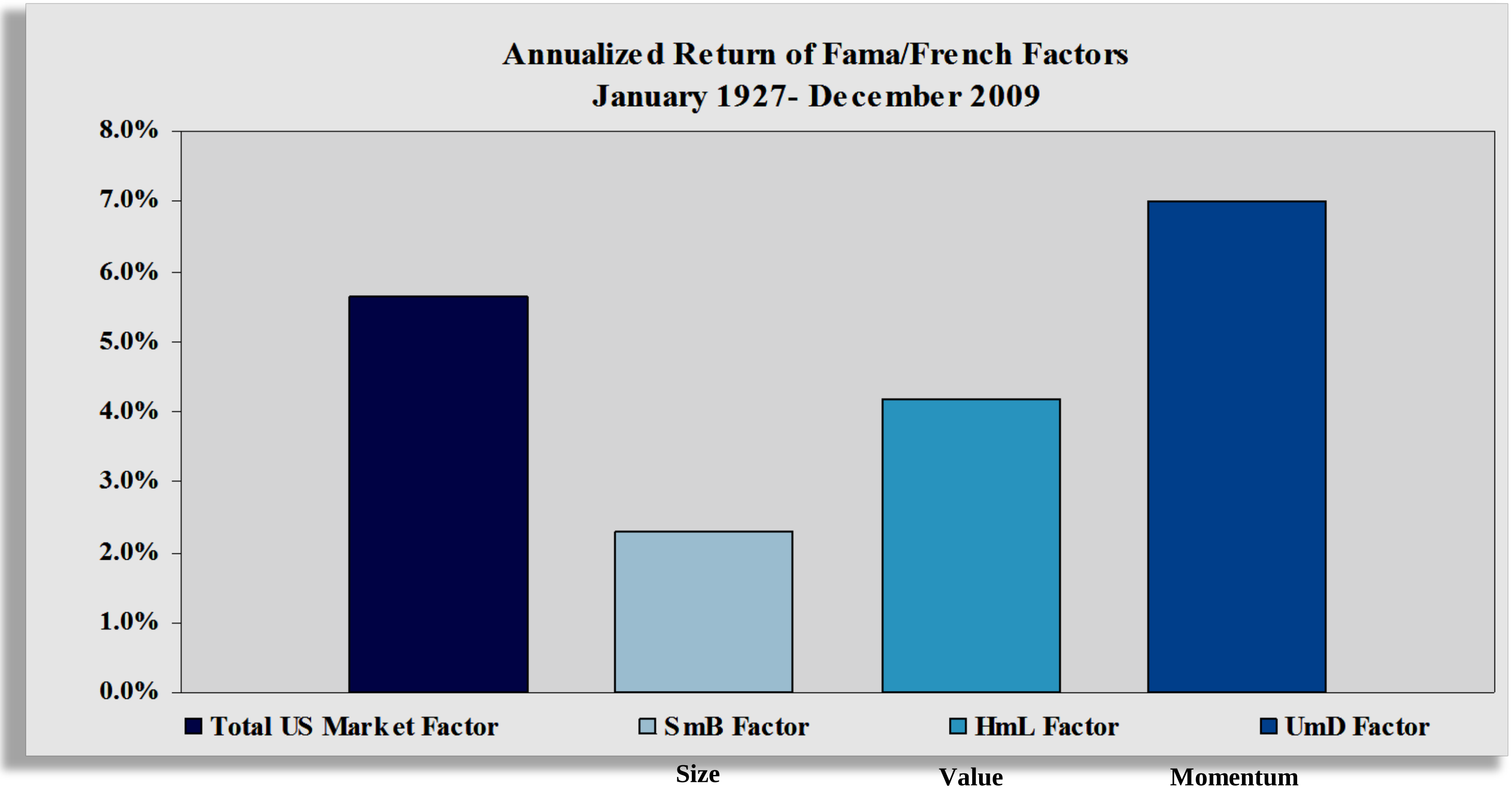
– Risk adjustment improves profits.

Grundy and Martin (2001)

**This will be important when considering the risk of these strategies later on.*

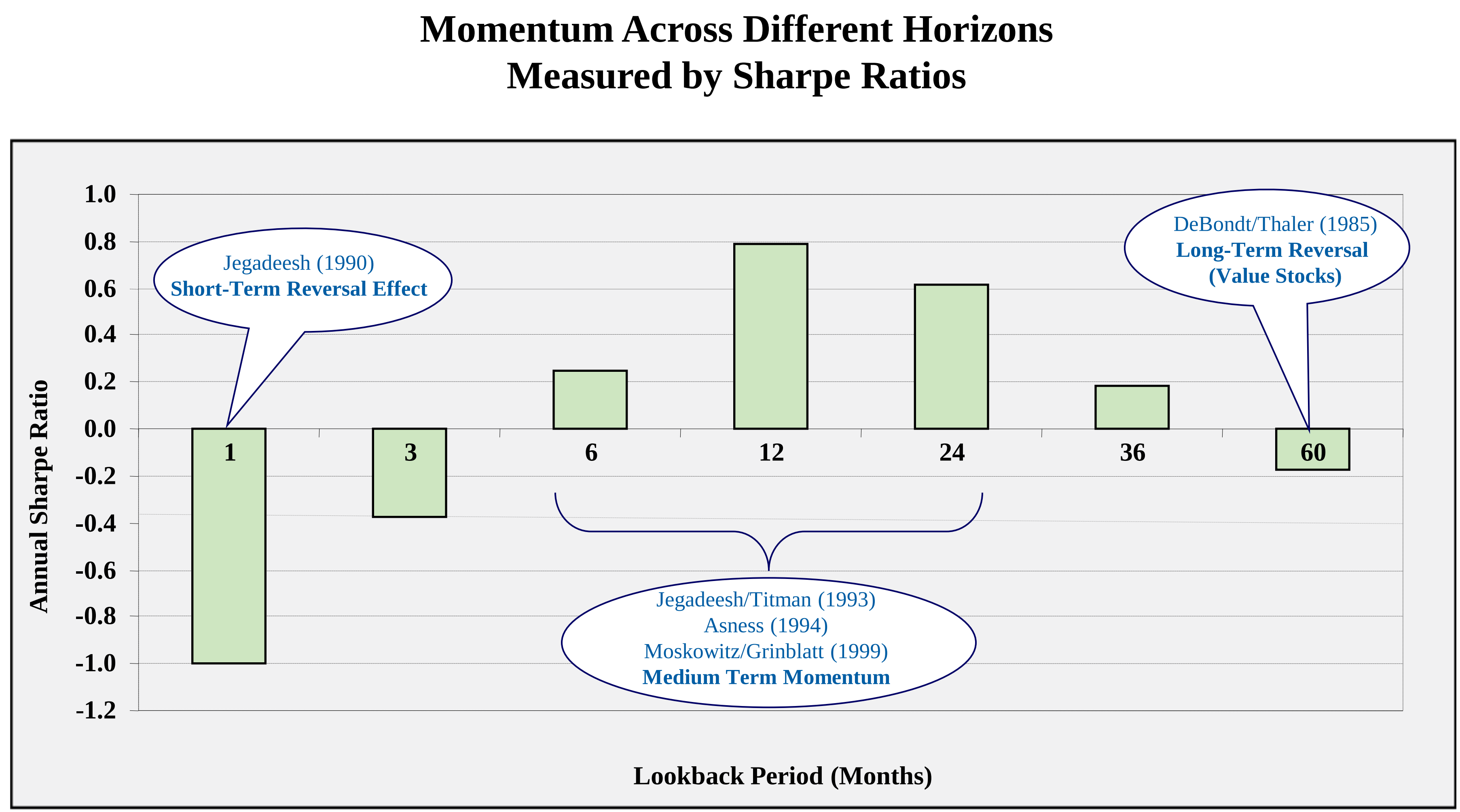
Momentum is the Fourth Factor

- Since the mid-1990s, the standard for any asset pricing study is to adjust for 4 factors (betas):



SmB Factor is a long-short portfolio composed of small stocks minus big stocks by market capitalization. HmL Factor is a long-short portfolio composed of stocks with high book to price valuations minus stocks with low book to price valuations. UmD is a long-short portfolio composed of stocks with positive momentum minus stocks with negative momentum by looking at the last twelve months price return excluding the last month. Past performance is not an indication of future performance.

Past Return Predictability over Horizons



Portfolios are formed looking back 1, 3, 6, 12, 24, 36 and 60 months and returns are computed with a 1 month holding period. Source: AQR Capital Management and papers noted above.

Possible Explanations

1. **Rational (risk-based)**
   – Time-varying expected returns
   – "Momentum" in the factors, or in the betas
   – A missing "momentum factor"

Problems:

- Stocks that rose (fell) are typically *less (more)* risky, implying the opposite pattern
- No momentum in the factors
- Sharpe ratio is very high

Risk Explanations

– Pays off in poor states of the economy

Momentum Profits (Monthly) During Good and Bad Times

	Market Risk Premium (Mkt - rf)	**Momentum Strategy (Winners - Losers)**
Bear Markets *(worst third market months)*	*-4.43%*	*1.46%*
Bull Markets *(best third market months)*	*5.17%*	*-0.03%*
Recessions *(defined by NBER)*	*-1.59%*	*0.89%*
Non-Recessions	*0.94%*	*1.16%*

Not much evidence for this kind of risk explanation.

Possible Explanations

2. **Behavioral**

- Gradual adjustment to news
  - Investors overreact to irrelevant information that develops gradually.
  - Investors tend to underreact to firm-specific information.
  - *Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1998)*
- Reference points (prospect theory and the disposition effect, tax-loss selling)

Possible Explanations

2. **Behavioral**

Problems:

- Near-arbitrage opportunities
  (is there “money on the table”?)
- All you need is *some* rational investors who are willing to exploit this
- (What) are there limits to arbitrage?

Not an Explanation

3. **<u>Data Mining</u>**

Problems:

- Works out of sample in

  other time periods,

  other markets,

  other asset classes.

Out of Sample Evidence

Individual stock momentum **Value-weighted**	**Full sample** **192701-201212**	**Out of sample** **192701-196412**	**Original sample** **196501-198912**	**Out of sample** **199001-201212**
mean	**0.75**	**0.64**	**0.83**	**0.93**
(t-stat)	**(4.85)**	**(2.60)**	**(4.03)**	**(2.85)**
Sharpe ratio	**0.16**	**0.12**	**0.23**	**0.19**
3-factor alpha	**1.09**	**1.03**	**1.00**	**1.17**
(t-stat)	**(7.91)**	**(5.23)**	**(4.84)**	**(3.27)**
Max. Sharpe ratio with FF factors	**0.30**	**0.28**	**0.38**	**0.37**

Out of Sample Evidence: Across Asset Classes

Performance of Momentum Across Asset Classes*
1972-2010

	Sharpe ratio of a long-short momentum strategy	Annualized return of a long-short momentum strategy	Sample period
Individual Stocks			
U.S.	0.45	6.8%	1972-2010
U.K.	0.47	7.1%	1972-2010
Europe	0.76	11.5%	1974-2010
Japan	0.12	1.8%	1974-2010
Global portfolio	0.68	10.2%	1972-2010
Other Asset Classes			
Equity indices	0.63	9.4%	1978-2010
Currencies	0.32	4.7%	1979-2010
Bonds	0.17	2.5%	1982-2010
Commodities	0.51	7.6%	1972-2010
Equal-weighted portfolio of other asset classes	0.65	9.7%	1972-2010
Equal-weighted portfolio of all asset classes	0.81	12.1%	1972-2010

*Source: Asness, Moskowitz and Pedersen, "Value and Momentum Everywhere", NBER Working Paper, 2011. Data updated through June 2010. The above uses a long-short portfolio to isolate the returns to momentum strategies from their respective directional market returns. Hypothetical long-short back-test where each momentum portfolio is scaled to an estimated 15% annualized volatility; gross of transaction and financing costs. Based on our research, the profits from these strategies survive transaction and financing costs. Hypothetical performance has inherent limitations.

Sources and Refinements

We will examine the empirical evidence on momentum to identify its sources.

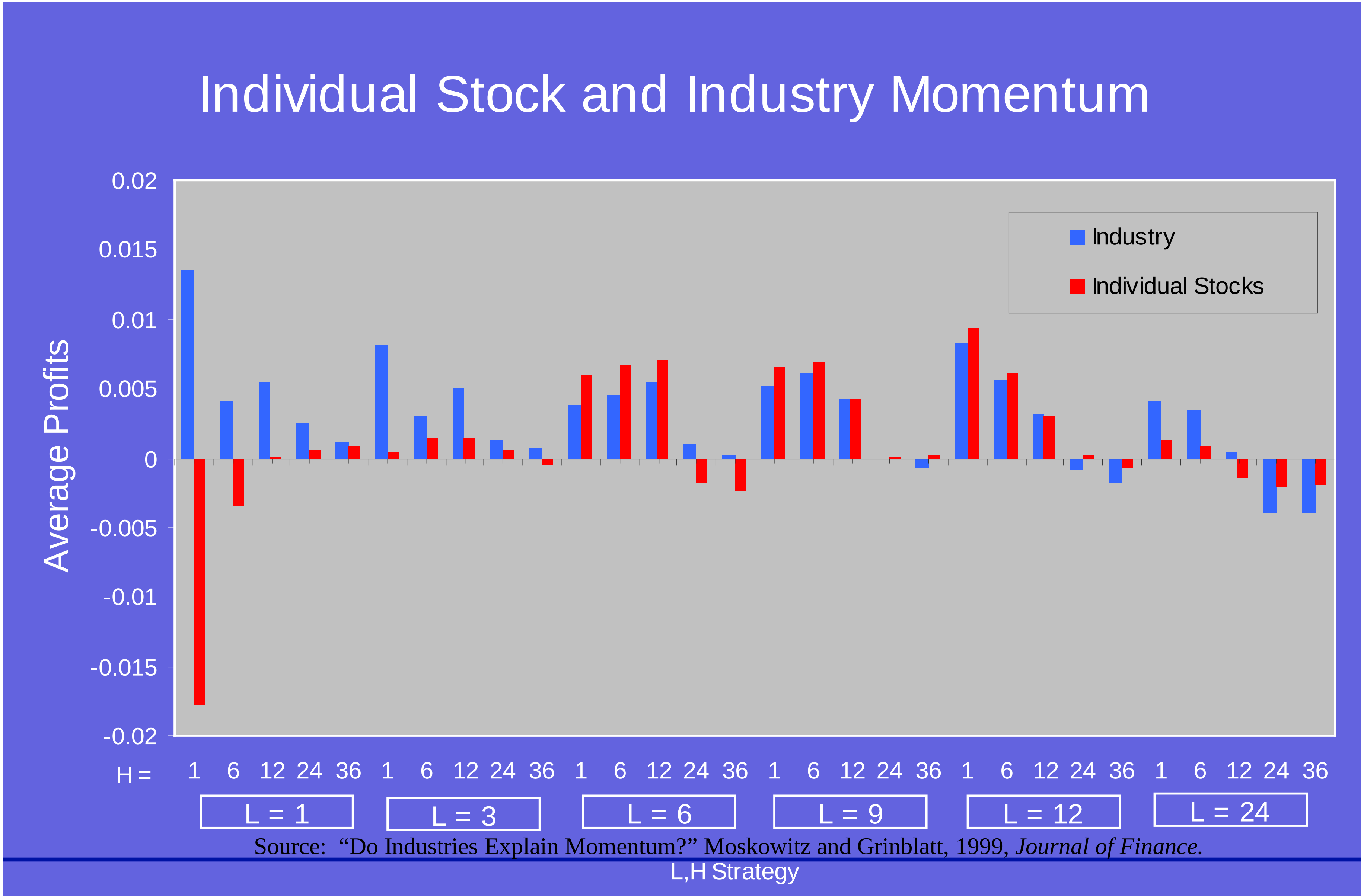
Industry effects and industry momentum

- There is strong momentum in industry portfolios.
- Just as profitable as individual stock momentum.
- Implies momentum strategy not well diversified.

Moskowitz and Grinblatt (1999)

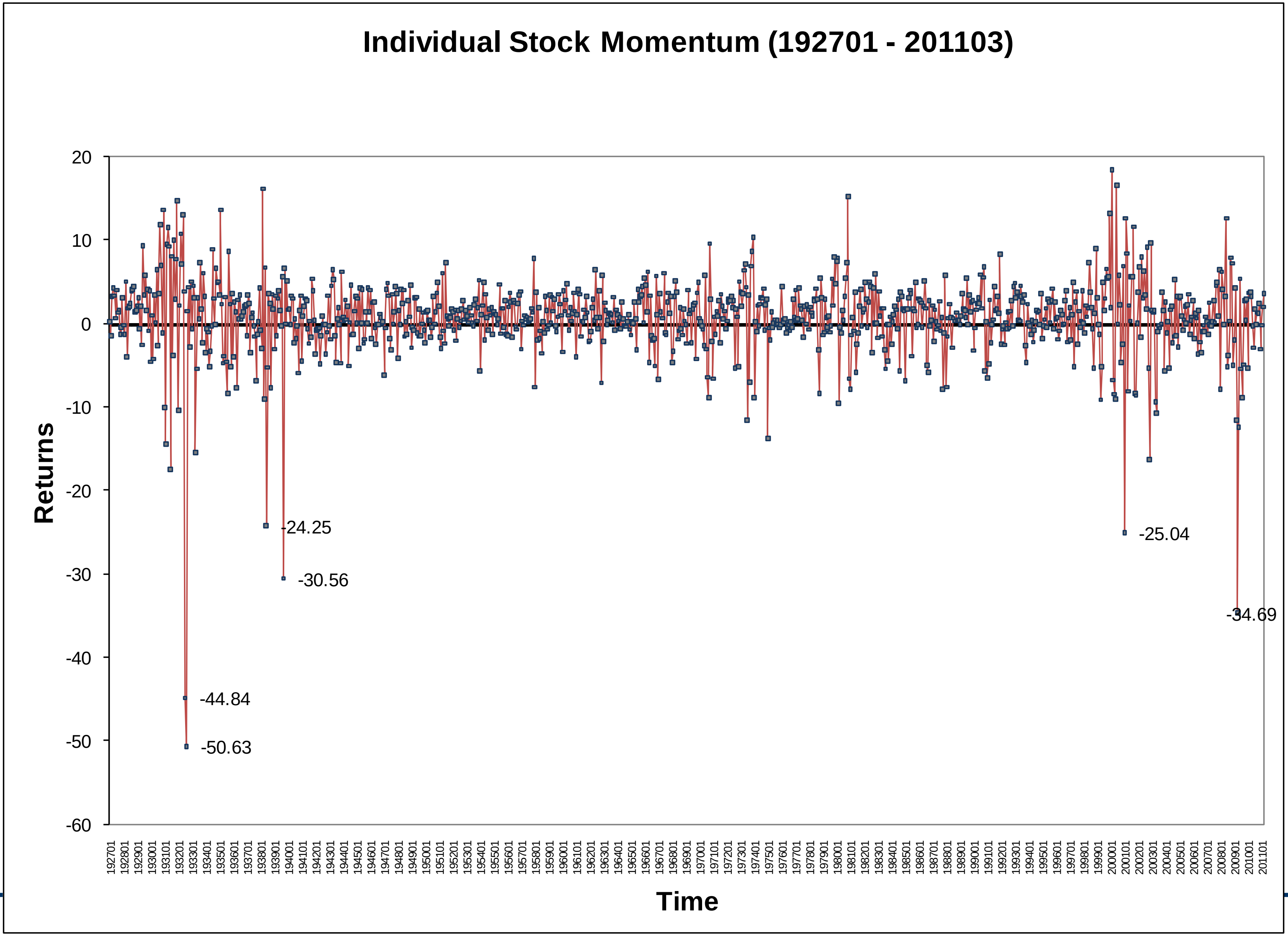
Helps with explanations as well as implementation.

Industry vs. Individual Stock Momentum

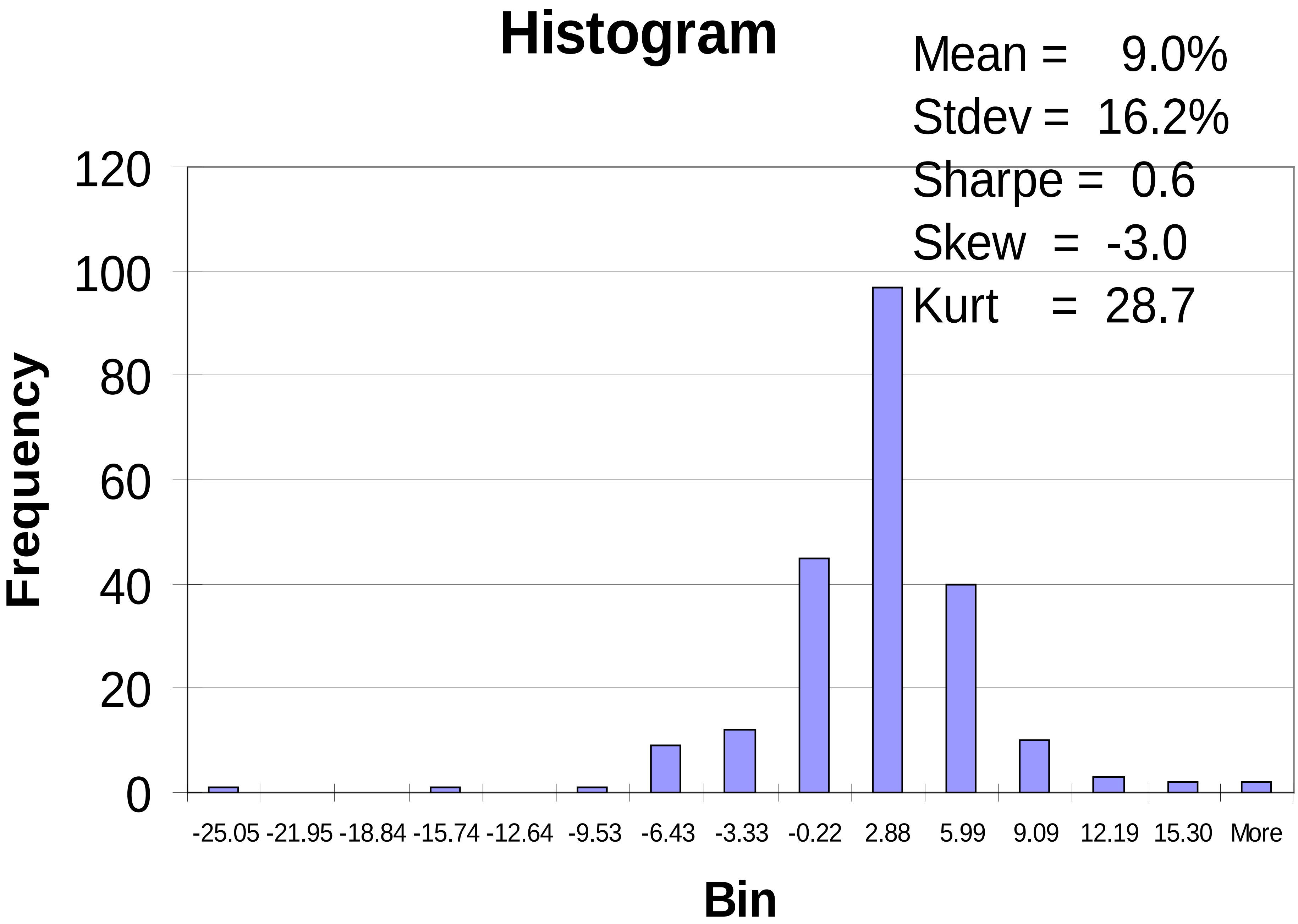


Source: "Do Industries Explain Momentum?" Moskowitz and Grinblatt, 1999, *Journal of Finance.*

Risk



Individual Stock Momentum (192701 - 201103)
Returns
Time
20
10
0
-10
-20
-30
-40
-50
-60
-24.25
-30.56
-44.84
-50.63
-25.04
-34.69


Histogram
Mean = 9.0%
Stdev = 16.2%
Sharpe = 0.6
Skew = -3.0
Kurt = 28.7
Frequency
120
100
80
60
40
20
0
-25.05 -21.95 -18.84 -15.74 -12.64 -9.53 -6.43 -3.33 -0.22 2.88 5.99 9.09 12.19 15.30 More
Bin

Risk

- Daniel and Moskowitz (2013) “Momentum Crashes”
- Momentum strategies experience large and persistent losses for some periods of time.
- Related to the conditional risk/betas of winners and (especially) losers
  - Kothari and Shanken (1992)---past returns related to beta
  - Grundy and Martin (2001)---examine for momentum
- Creates negative skewness in returns to momentum and option-like payoffs to momentum strategies
- Examine *t-12* to *t-2* momentum signal portfolios, rebalanced monthly, but calculate daily returns.
  - Daily returns useful for measuring conditional risk

Momentum

- However, momentum strategy returns exhibit significant negative skewness:
  - *e.g.*, in March-May 2009, equity momentum strategies suffered severe losses.
    - The April 2009 return was the worst since August, 1932.
  - Monthly momentum return skewness is -6.3.
    - For comparison, HML is +1.8, and the market is -0.58
- The maximum monthly momentum return in our sample is 26.1%.
  - The 5 worst are -79%, -60%, -46%, -44%, and -42%.
- Much like "carry-trade" strategies in currencies, momentum strategies are sometimes perceived like selling out-of-the money put options (see, *e.g.*, Brunnermeier, Nagel, and Pedersen (2008))

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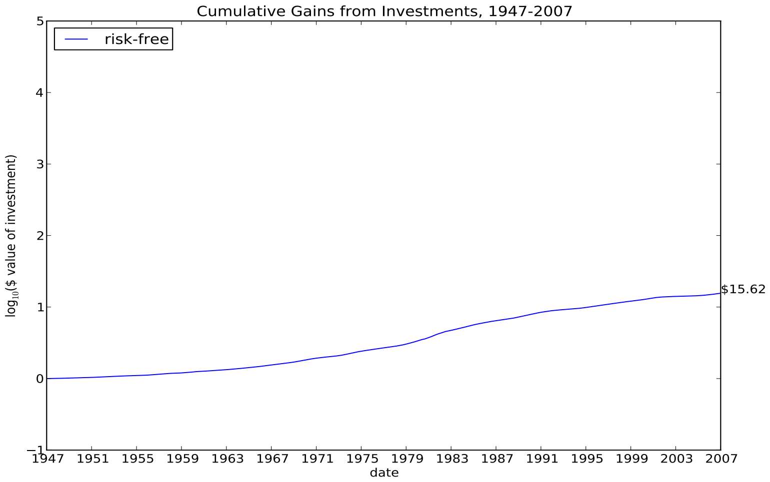
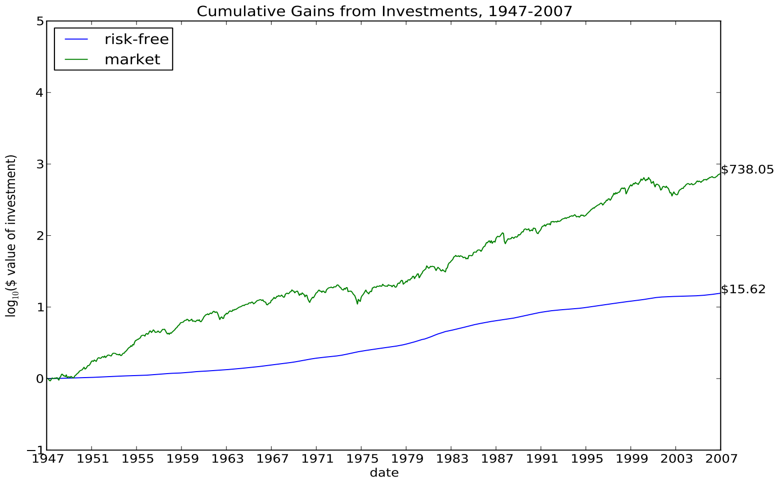
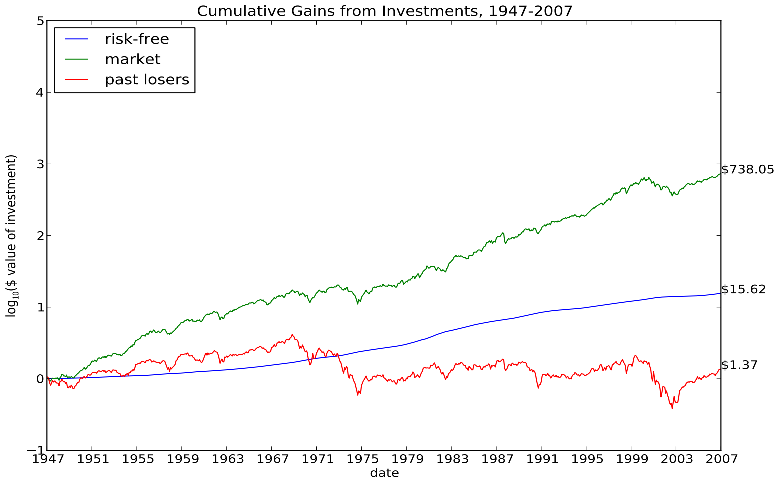
Long-Only Investment Strategy Returns



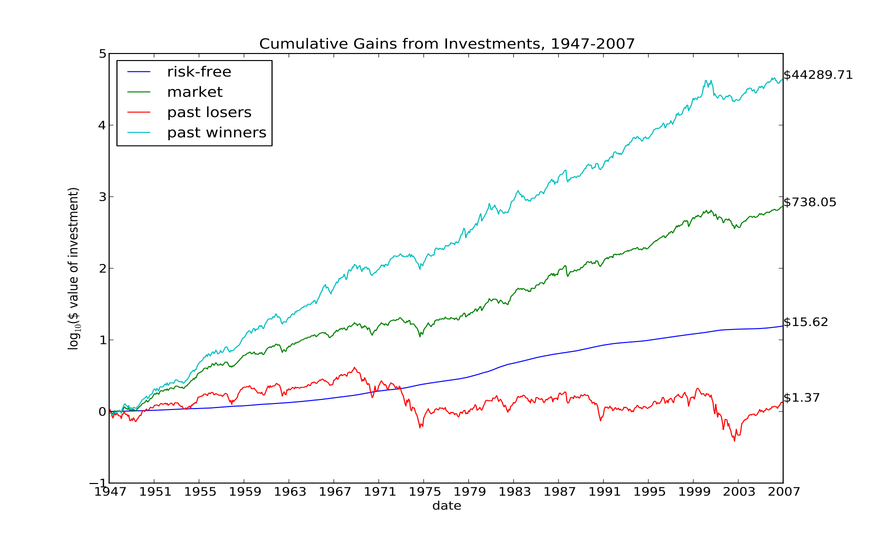
Long-Only Investment Strategy Returns



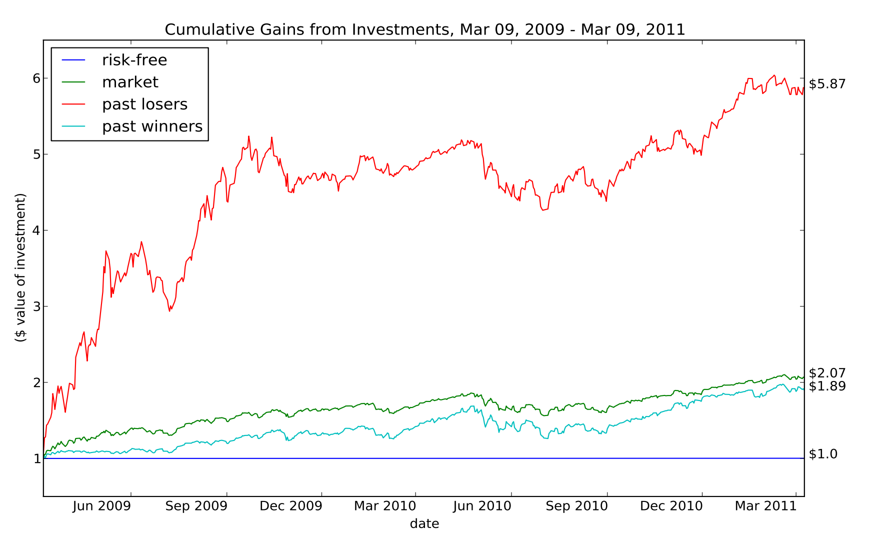
Long-Only Investment Strategy Returns



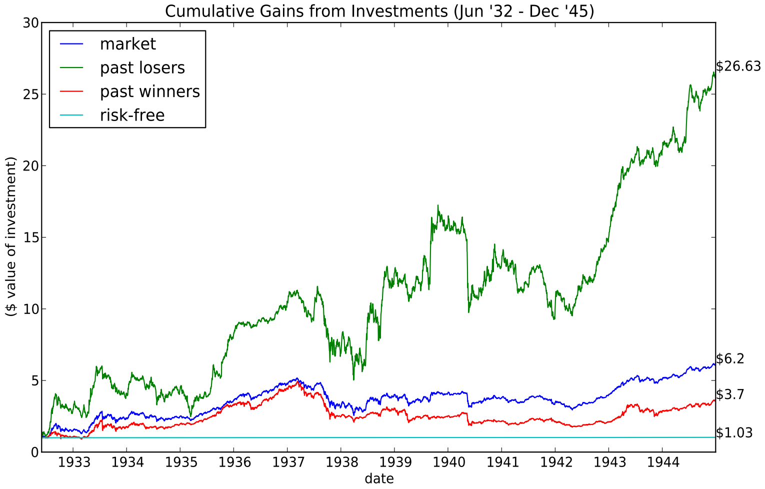
Long-Only Investment Strategy Returns



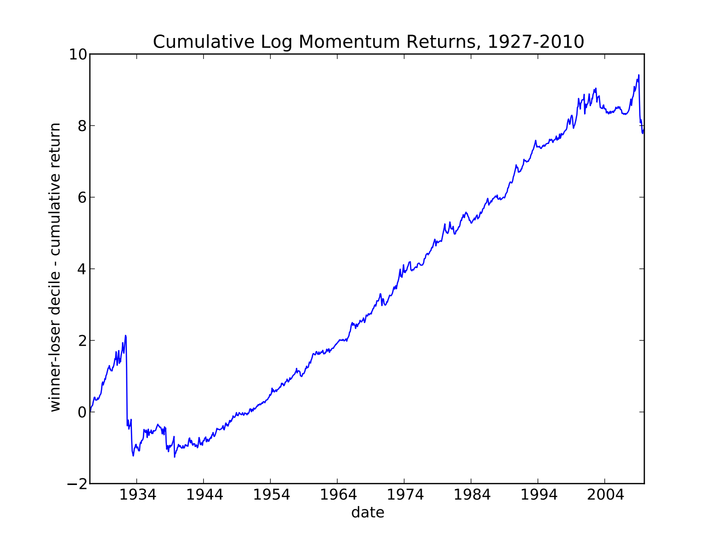
2009-10 Momentum Performance



Momentum in the Great Depression



Cumulative Momentum Returns



Momentum Portfolio Characteristics: *1927-2010*

	Momentum Decile Portfolios											
	1	2	3	4	5	6	7	8	9	10	wml	Mkt
μ	0.2	4.7	4.9	6.6	6.7	7.5	8.4	9.9	10.8	14.6	14.4	7.4
σ	34.4	28.7	24.7	22.6	21.0	20.4	19.5	18.8	19.8	22.7	27.7	18.9
α	-11.2	-5.1	-3.7	-1.4	-0.9	-0.0	1.3	3.1	3.7	7.2	18.4	0
$t(\alpha)$	(-5.8)	(-3.5)	(-3.2)	(-1.5)	(-1.1)	(-0.1)	(1.9)	(4.4)	(4.4)	(5.4)	(6.5)	(0)
β	1.56	1.34	1.18	1.10	1.03	1.03	0.97	0.93	0.96	1.01	-0.54	1
SR	0.01	0.17	0.20	0.29	0.32	0.37	0.43	0.53	0.54	0.64	0.52	0.39
sk(m)	0.13	-0.05	-0.12	0.17	-0.05	-0.32	-0.65	-0.53	-0.81	-0.92	-6.32	-0.58
sk(d)	-0.21	0.16	0.15	0.37	-0.10	0.02	-0.49	-0.58	-0.72	-0.74	-1.47	-0.44

- Note that the skewness is less pronounced for the daily returns than for the monthly.

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$t(\alpha)$	(-5.8)	(-3.5)	(-3.2)	(-1.5)	(-1.1)	(-0.1)	(1.9)	(4.4)	(4.4)	(5.4)	(6.5)	(0)
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10 Worst Monthly Momentum Returns

RANK	MONTH	MOM_t	MKT-2Y	MKT_t
1	1932-08	-0.7896	-0.6767	0.3660
2	1932-07	-0.6011	-0.7487	0.3375
3	2009-04	-0.4599	-0.4136	0.1106
4	1939-09	-0.4394	-0.2140	0.1596
5	1933-04	-0.4233	-0.5904	0.3837
6	2001-01	-0.4218	0.1139	0.0395
7	2009-03	-0.3962	-0.4539	0.0877
8	1938-06	-0.3314	-0.2744	0.2361
9	1931-06	-0.3009	-0.4775	0.1380
10	1933-05	-0.2839	-0.3714	0.2119
11	2009-08	-0.2484	-0.2719	0.0319

- MKT-2Y is the lagged 2-year market return
- MKT_t is the contemporaneous (1-month) market return.

Bear Market Momentum Performance

- The preceding table shows that the momentum strategy suffers its worst performance at "turning points," following large market declines:
  - In June 1932, the market "bottomed."
    - in July-August 1932, the market rose by 82%.
    - Over these 2 months, losers outperform winners by 206%.
    - *losers gain 236%, winners gain 30%.*
  - On March 9, 2009 the US equity market bottomed.
    - In March-May 2009, the market was up by 29%.
    - losers outperform winners by 149%.
    - *losers gain 156%, winners gain 6.5%.*

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Momentum Beta

- As of March 2009, many the firms in the Loser portfolio had fallen by 90% or more.
  - These were firms like Citigroup, Bank of America, Ford, GM, and International Paper (which was levered)
  - In contrast, the Winner portfolio was composed of defensive or counter-cyclical firms like Autozone.
- The loser firms, in particular, were often extremely levered, and at risk of bankruptcy.
  - Their common stock was effectively an out-of-the-money option on the firm value (*à là* (Merton 1974))
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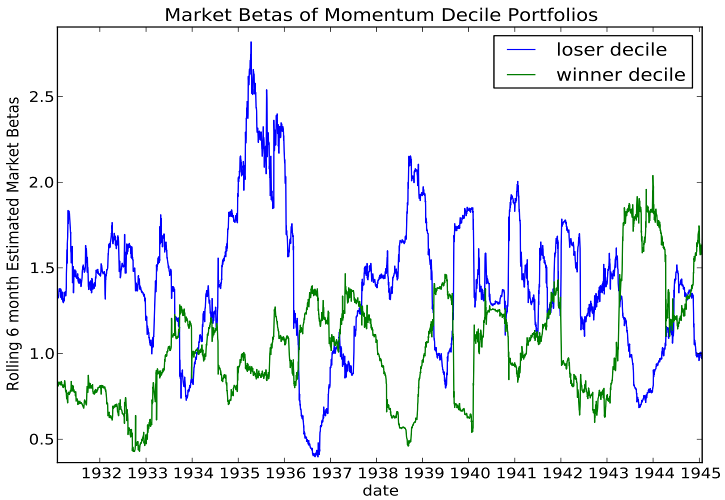
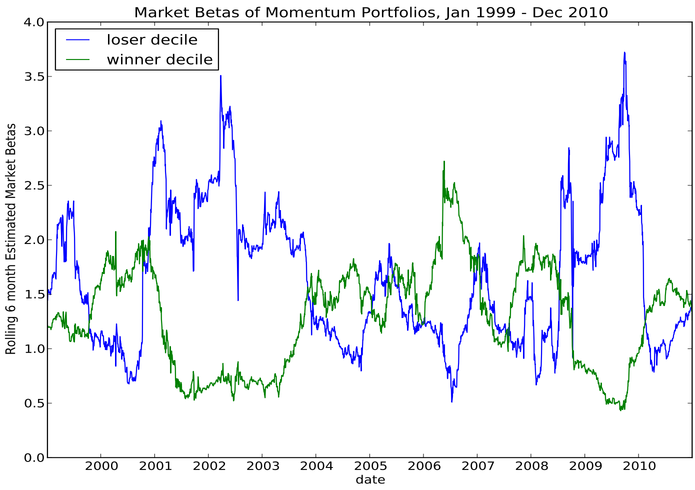
Market Beta and Momentum - 1931-1945



Market Beta and Momentum - 1999-2010



Hedging market risk

- Consistent with Grundy and Martin (2001), this evidence suggests hedging out market risk could be beneficial.
- We estimate rolling 42-day (2-month) betas
  - We regress $r_{WML,t}$ on contemporaneous market return, *and on 10 lags of the market return.*
    - The additional lags are particularly important in the early period, and for the low momentum portfolios, because of non-trading/illiquidity biases.
- We then construct a "hedged" WML portfolio:

$$\tilde{r}^{h}_{WML,t} = \tilde{r}_{WML,t} - \beta_t \cdot \tilde{r}^{e}_{m,t},$$

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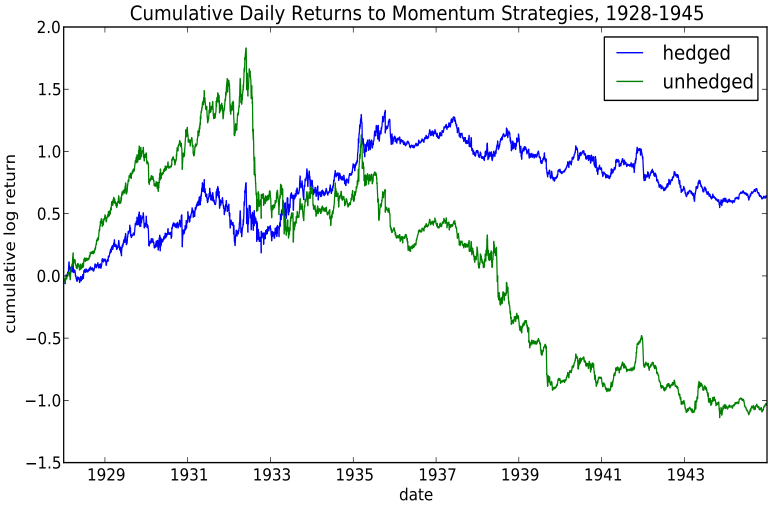
Hedged Momentum Portfolio Performance



Estimating Beta

There is a strong Up- and Down-β differential in bear markets:

$$\tilde{R}_{WML,t} = [\alpha_0 + \alpha_B \mathrm{I_B}] + \left[\beta_0 + \beta_B \mathrm{I_B} + \beta_{\mathrm{B,U}}(\mathrm{I_B} \cdot \tilde{\mathrm{I}}_{\mathrm{U}})\right] \tilde{R}^e_{m,t} + \tilde{\epsilon}_t$$

		Estimated Coefficients *(t-statistics in parentheses)*			
Coeff.	Variable	(1)	(2)	(3)	(4)
$\hat{\alpha}_0$	1	0.017	0.016	0.016	0.022
		(7.1)	(6.8)	(6.9)	(7.5)
$\hat{\alpha}_B$	I_B		-0.019	0.007	
			(-3.4)	(0.9)	
$\hat{\beta}_0$	$\tilde{R}^e_{m,t}$	-0.543	0.038	0.054	0.054
		(-12.6)	(0.7)	(0.7)	(0.7)
$\hat{\beta}_B$	$I_B \cdot \tilde{R}^e_{m,t}$		-1.198	-0.736	-0.788
			(-15.5)	(-6.1)	(-7.4)
$\hat{\beta}_{B,U}$	$I_B \cdot \tilde{I}_{\mathrm{U}} \cdot \tilde{R}^e_{m,t}$			-0.794	-0.695
				(-5.0)	(-6.0)
R^2_{adj}		0.136	0.321	0.339	0.339

- $\mathrm{I_B} = 1$ when the past 2-year market return is non-positive – *there are 177 Bear-market months.*
- $\tilde{\mathrm{I}}_{\mathrm{U}} = 1$ when $R_{m,t} > 0$. *This is not an* ex-ante *variable.*

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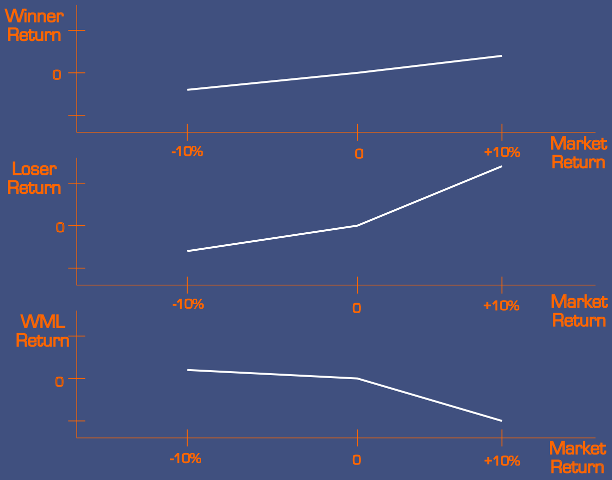
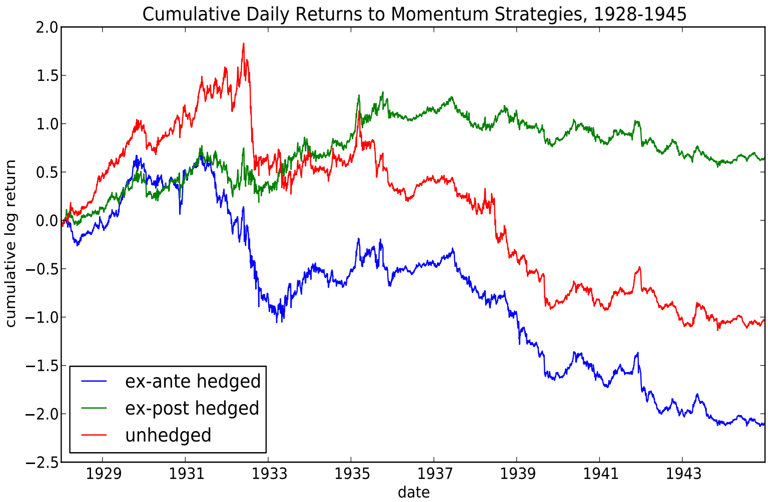
Where is the Option?

- This optionality is mostly in the loser portfolio:
  - For the past-loser portfolio, $\hat{\beta}_{B,U} = 0.60$.
  - For the past-winner portfolio, $\hat{\beta}_{B,U} = -0.21$.
- The optionality is not present in BulL markets:
  - For past-loser portfolio, $\hat{\beta}_{L,U} = 0.02$.

WML "Option"


Winner Return
0
-10%
0
+10%
Market Return
Loser Return
0
-10%
0
+10%
Market Return
WML Return
0
-10%
0
+10%
Market Return

Hedged Momentum Portfolio Performance



Forecasting Crashes

- We have seen that the payoff associated with the WML portfolio has short-option-like characteristics.
- It seems likely this this option will be more costly when market variance is higher
  - This would also be consistent with a behavioral motivation for our forecasting variable.
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Forecasting Momentum Returns

$$\tilde{r}_{WML,t} = \gamma_0 + \gamma_B \cdot \mathrm{I}_{B,t-1} + \gamma_{\sigma_m^2} \cdot \hat{\sigma}^2_{m,t-1} + \gamma_{int} \cdot \mathrm{I}_{B,t-1} \cdot \hat{\sigma}^2_{m,t-1} + \tilde{\epsilon}_t$$

	γ_0	γ_B	$\gamma_{\sigma_m^2}$	γ_{int}
1	0.0006	-0.0012		
	(5.59)	(-4.51)		
2	0.0008		-3.69	
	(6.78)		(-6.07)	
3	0.0009	-0.0006	-3.07	
	(6.98)	(-2.04)	(-4.54)	
4	0.0006			-4.75
	(6.06)			(-7.17)
5	0.0006	-0.0004	-0.54	-4.50
	(4.87)	(0.36)	(-0.53)	(-3.30)

Dynamic Strategy Returns

- We next evaluate the performance of a strategy which dynamically adjusts the weight on the basic wml strategy based on the forecast return and volatility of the wml strategy.
  - $E_{t-1}[r_{wml,t}]$ is forecast using the interaction on the preceding slide (regression 4)
  - $\hat{\sigma}^2_{wml,t-1}$ is forecast using a GARCH-like procedure applied to daily wml returns:
- The weight on wml at at the start of period t is:

$$\mathbf{w}_{wml,t-1} = \kappa \cdot \frac{E_{t-1}[r_{wml,t}]}{\hat{\sigma}^2_{wml,t-1}}$$

- Each strategy is scaled to give an unconditional volatility of 19%
  - equal to σ_{mkt} over the full sample.

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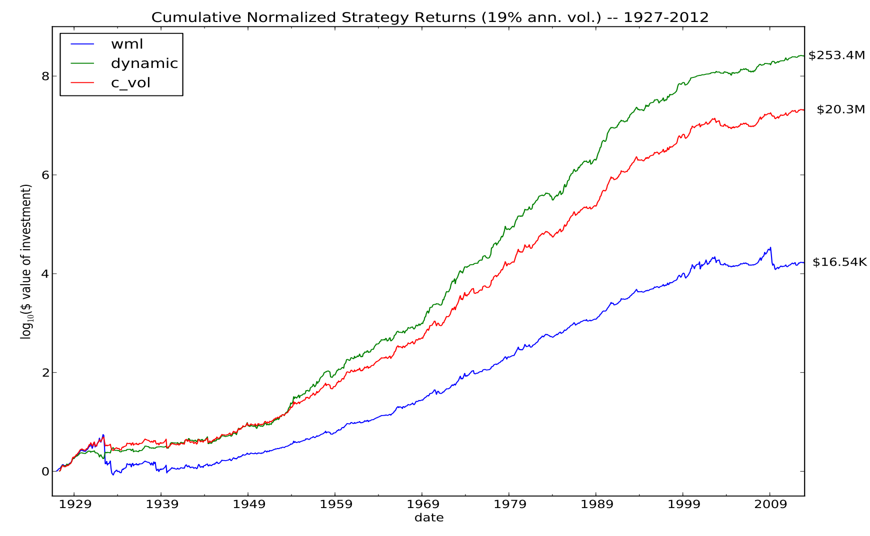
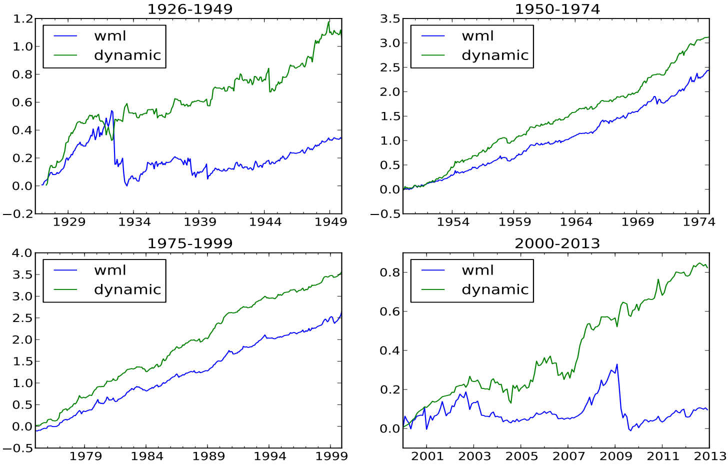
WML & Dynamic Strategy Returns



WML & Dynamic Strategy Returns - *Subsamples*



Dynamic Strategy Returns

period	wml	const σ	dynamic
1927-1950	0.137	0.397	0.578
1950-1975	0.897	1.035	1.335
1975-2000	0.927	1.085	1.386
2000-2011	0.020	0.219	0.625
1927-2011	0.524	0.865	1.124

- The dynamic strategy doubles the Sharpe Ratio of the static momentum strategy.
  - Moreover, the improvement is strong in each subperiod.
- A *constant volatility* strategy provides a substantial improvement over standard momentum.
  - See Barroso and Santa-Clara (2012).
- However, exploiting the strong forecastability of the mean gets you still superior performance.

Dynamic Strategy Returns

period	wml	const σ	dynamic
1927-1950	0.137	0.397	0.578
1950-1975	0.897	1.035	1.335
1975-2000	0.927	1.085	1.386
2000-2011	0.020	0.219	0.625
1927-2011	0.524	0.865	1.124

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Momentum in Other Markets

- We now investigate whether the predictability and optionality patterns are also present in other markets
- We examine 3 other equity markets, and 4 other asset classes.
  - Data is similar to that in Asness, Moskowitz, and Pedersen (2008).
- Our momentum measure is 12-2 in each market
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- We use a market return that corresponds to the asset universe in which the momentum strategy is constructed.
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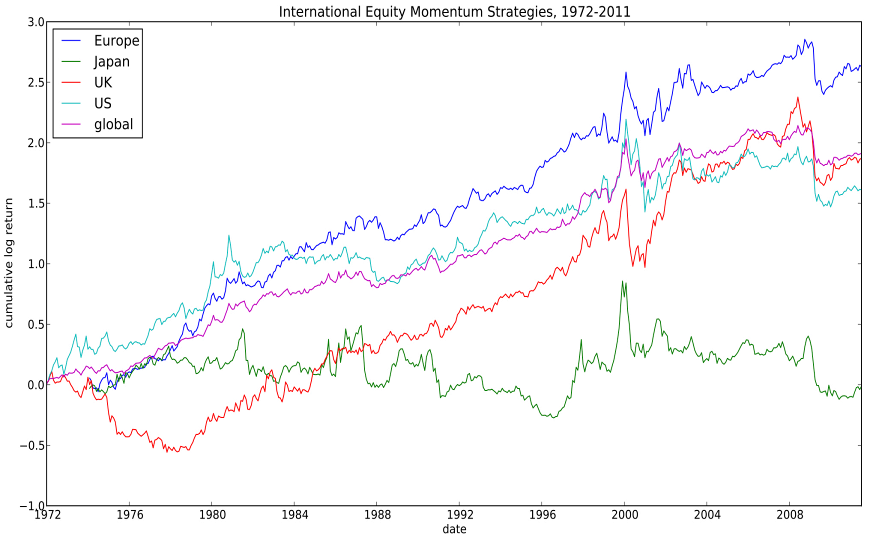
International Equity Market Momentum



Past Market Returns and Market Variance

$$\tilde{R}_t^{\mathrm{mom}} = [\alpha_0 + \alpha_B I_B + \alpha_V \hat{\sigma}_m^2] + [\beta_0 + \beta_B I_B + \beta_V \hat{\sigma}_m^2] \tilde{R}_{m,t}^e + \tilde{\epsilon}_t.$$

	Europe	Japan	UK	US	global
$\hat{\alpha}_0$	0.010	0.005	0.009	0.008	0.007
	(4.2)	(1.4)	(3.5)	(3.2)	(4.7)
$\hat{\alpha}_B$	0.003	0.002	-0.001	0.007	0.002
	(0.5)	(0.4)	(-0.1)	(1.2)	(0.4)
$\hat{\alpha}_V$	-0.143	-0.150	-0.141	-0.197	-0.116
	(-2.7)	(-2.3)	(-2.3)	(-3.3)	(-3.1)
$\hat{\beta}_0$	0.109	0.242	0.069	0.216	0.052
	(2.4)	(4.4)	(1.6)	(3.6)	(1.4)
$\hat{\beta}_B$	-0.372	-0.539	-0.092	-0.523	-0.201
	(-4.3)	(-6.8)	(-1.2)	(-5.0)	(-2.8)
$\hat{\beta}_V$	-1.787	0.449	-2.390	-1.836	-1.011
	(-3.0)	(0.5)	(-2.9)	(-2.1)	(-1.9)

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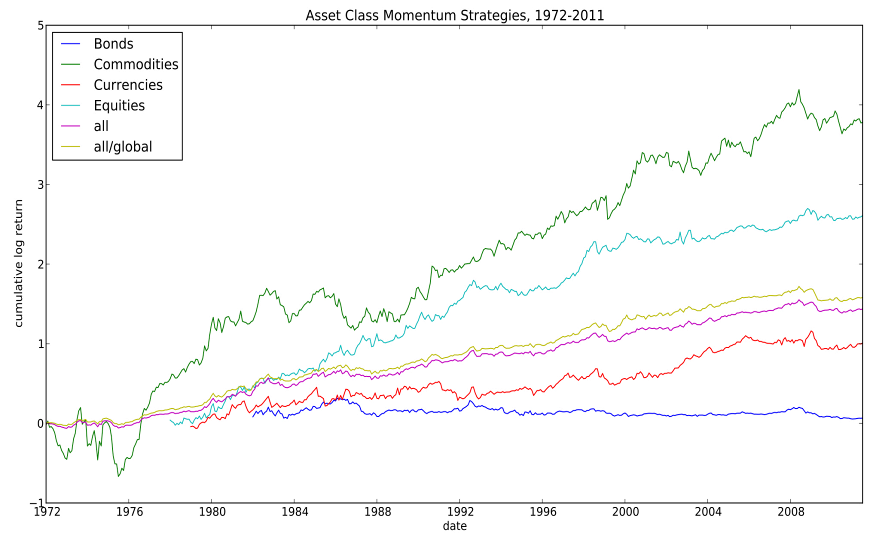
Optionality in Bear Markets

$$\tilde{R}_t^{mom} = [\alpha_0 + \alpha_B \mathrm{I_B}] + \left[\beta_0 + \beta_B \mathrm{I_B} + \beta_{\mathrm{B,U}}(\mathrm{I_B} \cdot \tilde{\mathrm{I}}_\mathrm{U})\right] \tilde{R}_{m,t}^e + \tilde{\epsilon}_t$$

	Europe	Japan	UK	US	global
$\hat{\alpha}_0$	0.007	-0.001	0.006	0.003	0.005
	(3.0)	(-0.3)	(2.6)	(1.2)	(3.2)
$\hat{\alpha}_B$	0.012	0.013	0.004	0.005	0.005
	(1.8)	(1.8)	(0.6)	(0.5)	(1.0)
$\hat{\beta}_0$	0.075	0.248	0.026	0.167	0.029
	(1.7)	(4.7)	(0.6)	(2.9)	(0.8)
$\hat{\beta}_B$	-0.305	-0.284	0.016	-0.556	-0.092
	(-2.6)	(-2.0)	(0.1)	(-3.2)	(-0.9)
$\hat{\beta}_{B,U}$	-0.443	-0.392	-0.329	-0.085	-0.338
	(-2.5)	(-2.1)	(-2.2)	(-0.3)	(-2.2)

Other Asset Class Momentum



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	Bonds	Commod's	Currencies	Equities	all	all+stock
$\hat{\alpha}_0$	0.001	0.013	0.006	0.008	0.004	0.005
	(1.2)	(3.2)	(2.8)	(3.8)	(4.4)	(5.5)
$\hat{\alpha}_B$	-0.000	-0.007	-0.009	-0.001	-0.001	0.000
	(-0.0)	(-1.0)	(-3.0)	(-0.2)	(-0.4)	(0.0)
$\hat{\alpha}_V$	-0.029	-0.059	-0.013	-0.020	-0.025	-0.049
	(-1.4)	(-0.7)	(-0.4)	(-0.5)	(-1.2)	(-2.3)
$\hat{\beta}_0$	0.290	0.250	0.267	0.300	0.188	0.109
	(3.7)	(2.7)	(2.9)	(6.2)	(2.7)	(2.3)
$\hat{\beta}_B$	-0.448	-0.718	-0.987	-0.585	-0.360	-0.238
	(-2.9)	(-4.1)	(-7.3)	(-7.0)	(-2.6)	(-2.4)
$\hat{\beta}_V$	-1.145	0.876	0.173	-0.957	-1.558	-1.363
	(-0.8)	(0.5)	(0.2)	(-1.4)	(-1.5)	(-1.9)

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	Bonds	Commod's	Currencies	Equities	all	all+stock
$\hat{\alpha}_0$	-0.002	0.009	0.003	0.005	0.002	0.003
	(-1.5)	(2.4)	(1.7)	(2.4)	(2.3)	(3.4)
$\hat{\alpha}_B$	0.005	0.017	0.008	0.010	0.008	0.007
	(1.5)	(1.8)	(2.0)	(2.1)	(2.7)	(2.3)
$\hat{\beta}_0$	0.287	0.288	0.302	0.283	0.183	0.094
	(4.5)	(3.7)	(3.4)	(6.1)	(2.8)	(2.1)
$\hat{\beta}_B$	-0.346	0.040	-0.498	-0.474	0.260	-0.024
	(-0.9)	(0.1)	(-1.8)	(-4.2)	(0.8)	(-0.2)
$\hat{\beta}_{B,U}$	-0.211	-1.327	-0.889	-0.338	-1.138	-0.692
	(-0.4)	(-2.6)	(-2.4)	(-1.9)	(-2.7)	(-3.2)

Conclusions & Future Work

1. In “normal” environments, the market appears to underreact to public information, resulting in consistent price momentum.
2. However, in extreme market enviroments, the market prices of severe past losers embody a very high premium.
    - When market conditions ameliorate, these losers experience strong gains, resulting in a momentum crash.
        - The expected gains from the loser portfolio are related to both past market losses, and lagged market volatility.
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Risk

- Risks at certain times can be very high

- Large and persistent losses in some years

  *Poor performance in 2000-2003 (value did well)

  *Spring of 2009 was a disaster

- Far from a pure arbitrage

  *Industry/sector exposure makes it less diversified

  *Introduces additional tracking error

- Highest momentum stocks may also be overpriced

- Are Sharpe ratios the right metric?

Sources and Refinements

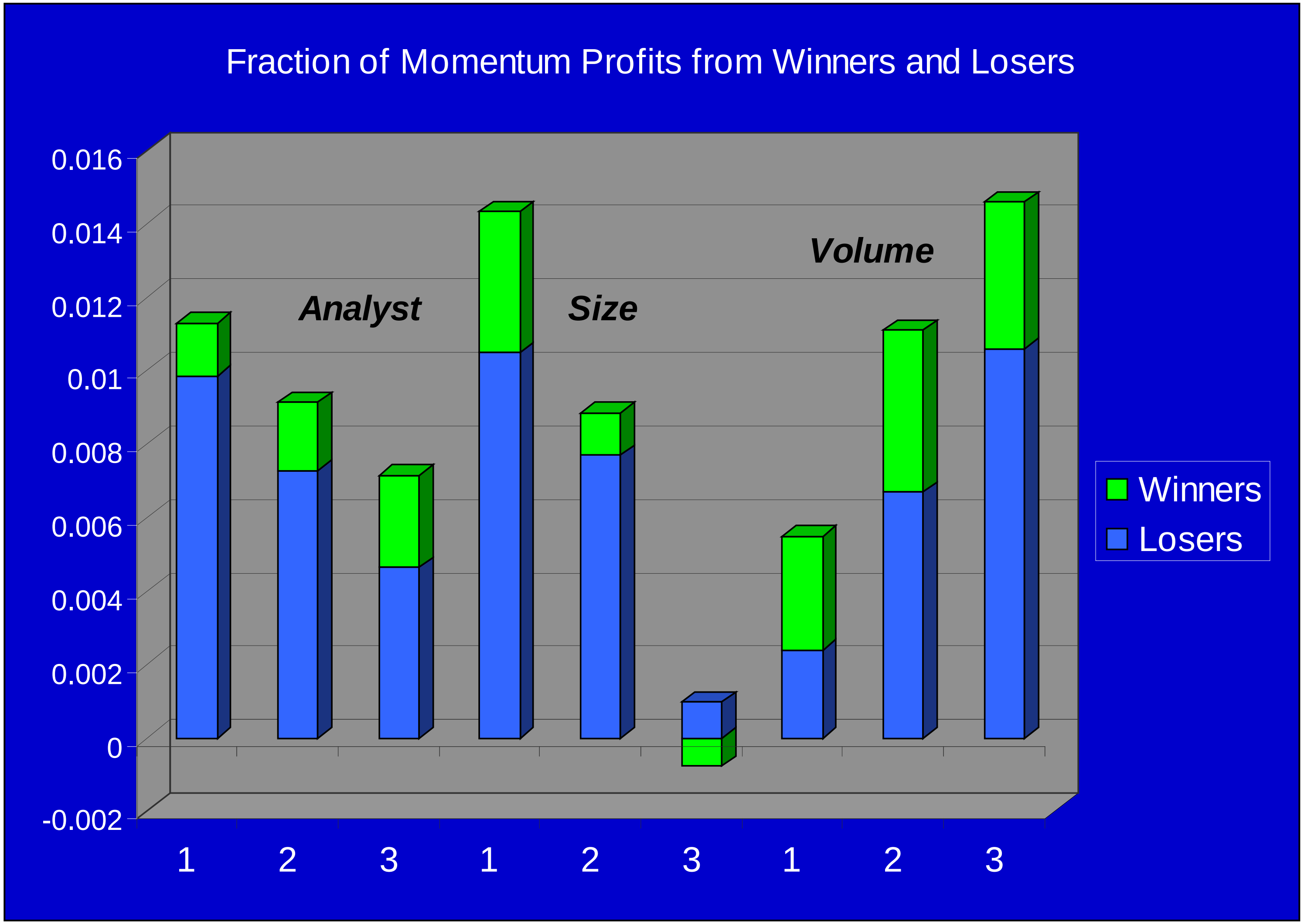
- Size and analyst coverage
  Hong, Lim, and Stein (1999)

- Trading volume (turnover)
  Lee and Swaminathan (2000)

- Value and growth stocks
  Asness (1997)

- ***Robustness of these effects***
  Israel and Moskowitz (2013)

Sources and Refinements



Source: "Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies," Hong, Lim, and Stein, 1999, *Journal of Finance*; "Price Momentum and Trading Volume," Lee and Swaminathan, 2000, *Journal of Finance.*

Sources and Refinements

- Behavioral view: momentum stronger when news is less obvious and harder to analyze:
  small, little analyst coverage, growth, widely dispersed analyst forecasts, volatile

- Momentum stronger when news is bad and therefore not publicized by the firm or analysts

- Momentum stronger when rational arbitrageurs face higher transactions costs.

Other Underreaction Phenomena

- Post earnings announcement drift
- Dividend announcements
- Disposition effect
  - Grinblatt and Han (2005)
  - Frazzini (2006)
- Trading patterns
- Cross-stock momentum

Other Momentum Phenomena

Earnings momentum

- PEAD – following earnings surprises
- Earnings momentum – revision in analysts' earnings forecasts
- Price and earnings momentum are distinct
- Combining the two creates an even more profitable trading strategy
- Observed in 34 international markets

Disposition effect
(and its relation to momentum)

The **disposition effect** is the tendency to sell securities that have gone up, not down, in value since purchase

- **Mental Accounting**: define "gain" or "loss" as the current price minus purchase price

- **Prospect Theory**: investors risk averse over gains and risk seeking in losses -- tend to sell if price up since purchase, and hold on to assets that have gone down

Disposition Effect

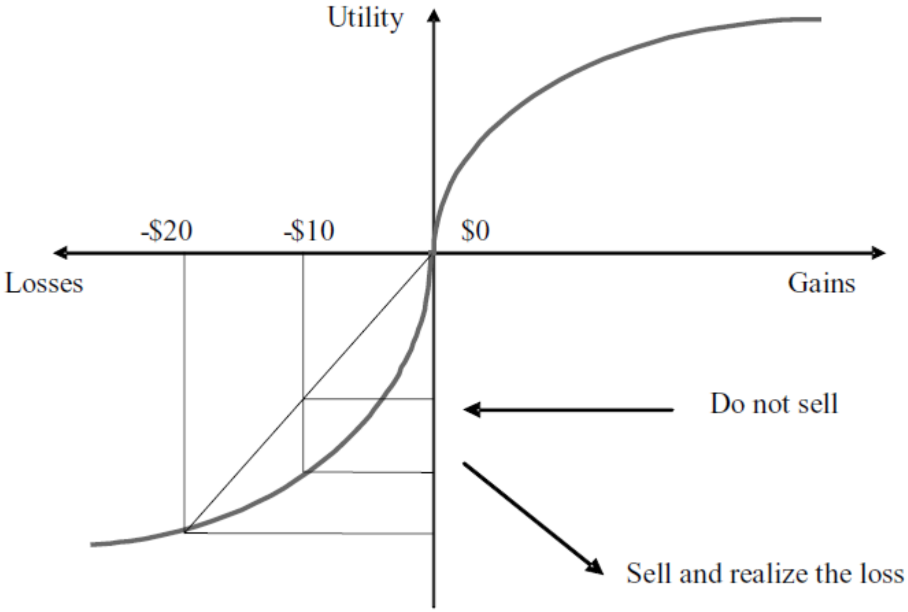


Figure 1. Prospect theory, mental accounting, and the disposition effect: Realize a loss. Assume that an investor purchased one share at $50 and the price is now $40. Suppose that in the next month, the price could go either up $10 or down $10 (with equal probability). The investor must choose between selling the stock now and realizing a paper loss of $10, or keeping the stock in his portfolio. This figure shows the utility gain (loss) of the two alternatives.

Disposition Effect

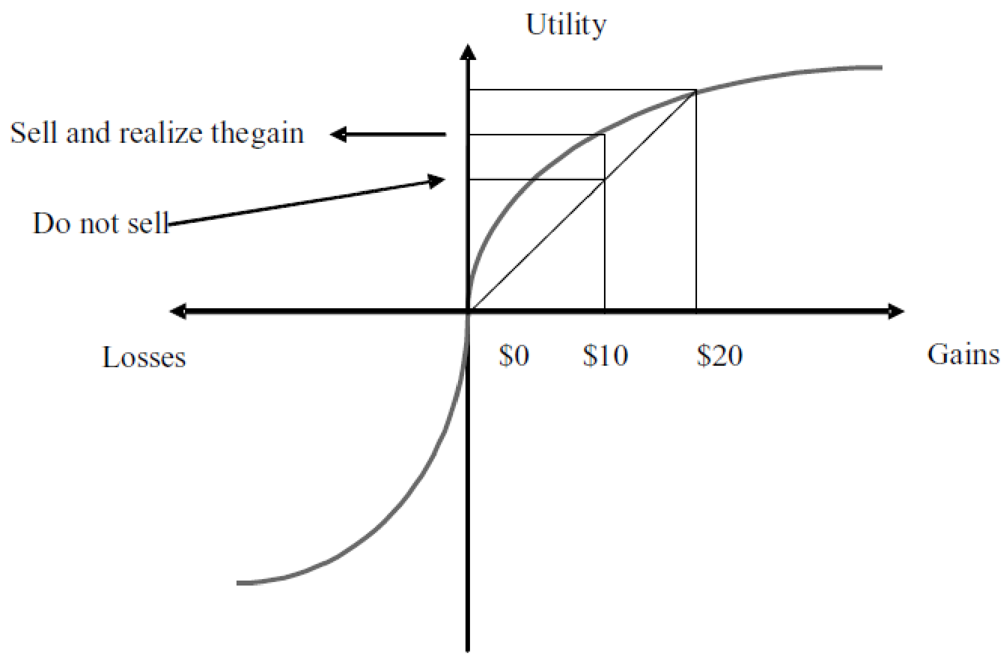


Figure 2. Prospect theory, mental accounting, and the disposition effect: Realize a gain. Assume that an investor purchased one share at $50 and the price is now $60. Suppose that in the next month the price could go either up $10 or down $10 (with equal probability). The investor must choose between selling the stock now and realizing a paper gain of $10, or keeping the stock in his portfolio. This figure shows the utility gain (loss) of the two alternatives.

Frazzini (2006)

– Price drift is severe when news and capital gains overhang have the same sign

– Magnitude of drift is related to amount of unrealized capital gains prior to event

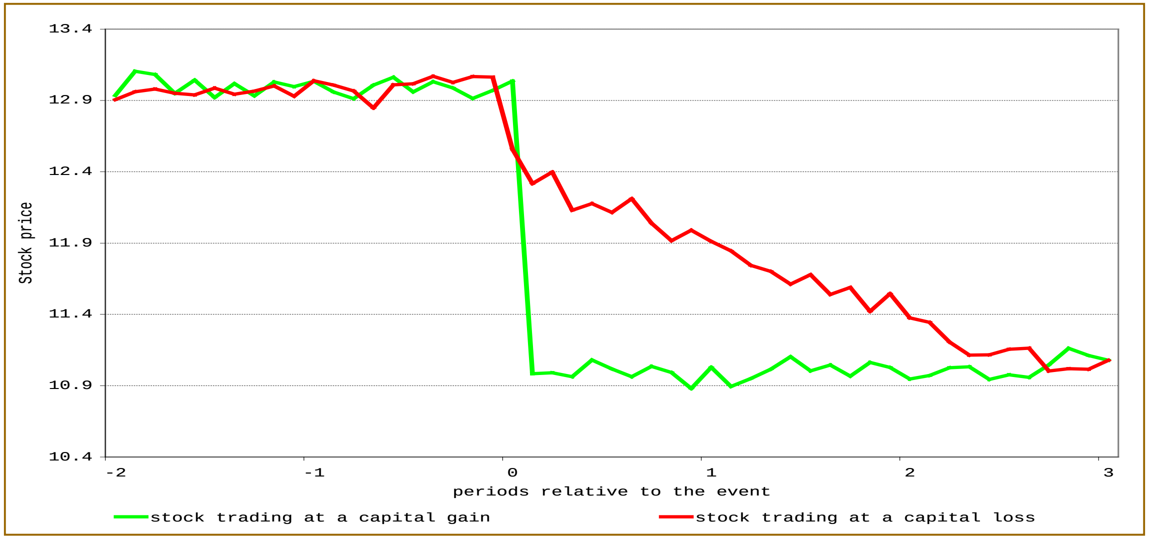
Underreaction to bad news more severe when current holders are facing a capital loss

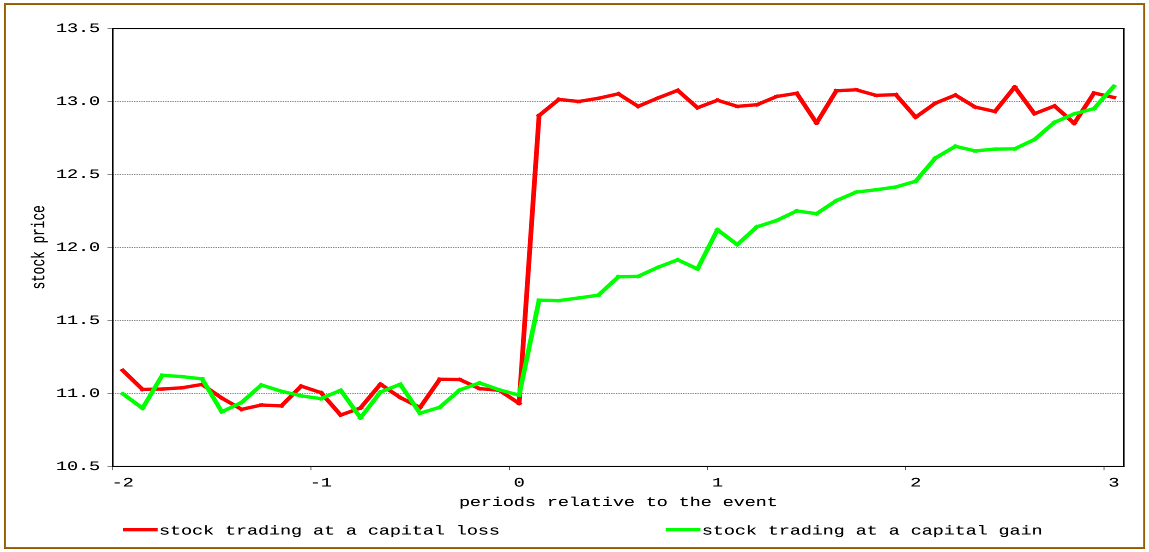
Underreaction to good news more severe when current holders are facing a capital gain

– Capital gains overhang is the deviation of the current price from the reference price:

$$g_t = \frac{P_t - RP_t}{P_t}$$

using mutual fund quarterly portfolio positions.


13.4
12.9
12.4
11.9
11.4
10.9
10.4
Stock price
-2
-1
0
1
2
3
periods relative to the event
stock trading at a capital gain
stock trading at a capital loss


13.5
13.0
12.5
12.0
11.5
11.0
10.5
stock price
-2
-1
0
1
2
3
periods relative to the event
stock trading at a capital loss
stock trading at a capital gain

Frazzini (2006)

	Overhang spread			Negative overhang spread		
Rolling period (months)	Bad news Losses	Good news Gains	L/S	Bad news Gains	Good news Losses	L/S
+1	-0.980	1.110	2.077	-0.453	0.347	0.798
	[-3.04]	[5.86]	[5.45]	[0.96]	[-1.60]	[1.84]
+2	-1.072	1.429	2.486	-0.003	-0.129	-0.123
	[-2.82]	[7.39]	[5.54]	[-0.38]	[-0.01]	[-0.27]
+3	**-1.129**	**1.304**	**2.433**	**-0.245**	**-0.152**	**0.092**
	[-3.51]	[9.56]	[6.60]	[-0.57]	[-1.61]	[0.28]

		Overhang spread			Negative overhang spread		
		Bad news	Good news	L/S	Bad news	Good news	L/S
A	Low mutual fund ownership	**-1.098**	**1.337**	**2.435**	-0.284	0.010	0.275
		(-2.95)	(8.16)	(6.28)	(0.03)	(-1.59)	(0.85)
B	High mutual fund ownership	**-1.083**	**1.202**	**2.284**	-0.083	-0.222	-0.140
		(-3.88)	(8.33)	(6.49)	(-0.87)	(-0.55)	(-0.42)
C	Only index funds	**-0.293**	0.348	**0.641**	**-0.285**	**0.313**	**0.599**
		(-2.43)	(1.45)	(2.70)	(-2.56)	(1.99)	(2.81)
D	Turnover-based gains, 1963-1979	**-1.014**	**1.533**	**2.547**	0.202	0.213	0.012
		(-2.61)	(5.48)	(5.01)	(0.58)	(0.69)	(0.03)
E	Turnover-based gains, 1980-2003	**-0.559**	**1.361**	**1.920**	-0.141	0.299	0.440
		(-2.36)	(7.40)	(4.79)	(0.93)	(-0.75)	(1.67)
F	Characteristics matched returns	**-0.920**	**0.931**	**1.851**	0.011	-0.014	-0.025
		(-4.30)	(3.32)	(5.60)	(0.90)	(-0.04)	(-0.04)
G	Standardized unexpected earnings	**-0.672**	**1.066**	**1.738**	-0.049	0.278	0.339
		(-2.52)	(8.28)	(5.26)	(0.99)	(-0.27)	(0.97)
H	Analysts' revisions	**-1.568**	**1.193**	**2.761**	0.159	-0.652	-0.811
		(-2.07)	(3.43)	(2.84)	(-0.95)	(0.53)	(-1.01)

What do trading patterns look like?

- Trading imbalances
  1. Large trades
  2. Small trades

- At the turn-of-the-year

- Use transaction price relative to bid-ask midpoint to *sign* trades (measure of buying or selling pressure)
  - *Lee and Ready (1991) algorithm*

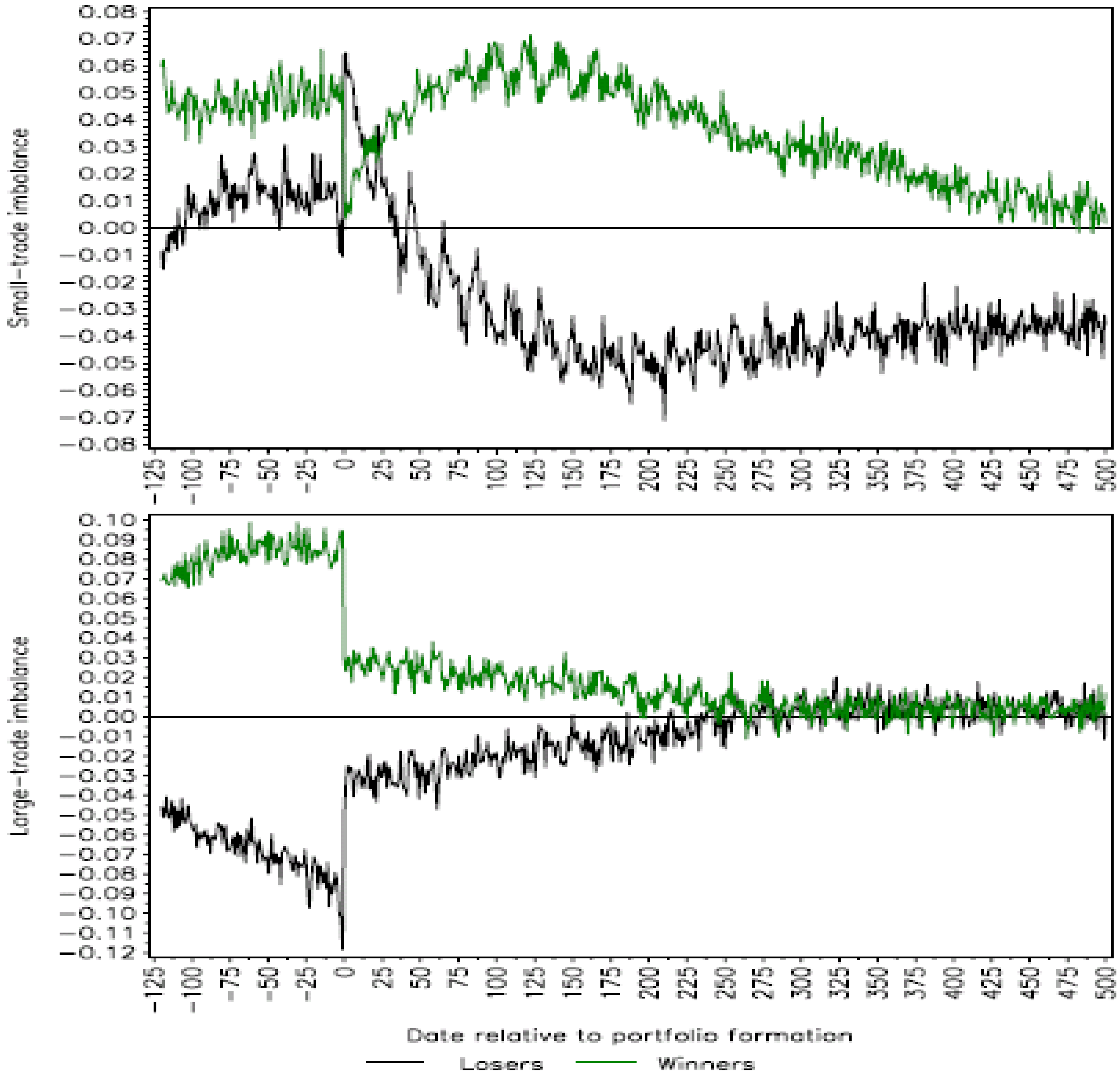


Figure 1: Trade imbalances: Small and large trades

Other Momentum Phenomena

Momentum across securities:

- from high volume to low volume firms *(Chordia and Swaminathan (2000))*
- from stock to bond markets *(Gebhardt, Hvidkjaer, and Swaminathan (2005))*
- *from industries to their suppliers and customers *(Menzly and Ozbas (2004))*
- *from customers to their suppliers *(Cohen and Frazzini (2008)*

**More on these later.*

Conclusions

- Is momentum a real phenomenon, or will it disappear?

- Is momentum tied to risk or behavior?
  - Other measures of risk might be important (crash risk, higher moments)
  - Which behavioral theories are most promising?
  - Transactions costs have declined, which implies it is easier to exploit momentum.
  - Will momentum be weaker going forward?
  - Increasing amounts of capital exploiting momentum could affect its profitability.