

Lecture 10 : Hedge Funds



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Hedge Funds vs. Mutual Funds

Hedge Fund

- Transparency: Limited Liability Partnerships that provide only minimal disclosure of strategy and portfolio composition
- Less than 100 investors unless “qualified”

Mutual Fund

- Transparency: Regulations require public disclosure of strategy and portfolio composition
- Number of investors is not limited



Hedge Funds vs. Mutual Funds

Hedge Fund

- Investment strategy: Very flexible, funds can act opportunistically and make a wide range of investments
- Often use shorting, leverage, options

Mutual Fund

- Investment strategy: Predictable, stable strategies, stated in prospectus
- Limited use of shorting, leverage, options



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Hedge Funds vs. Mutual Funds

Hedge Fund

- Compensation structure: Typically charge a management fee of 1-2% of assets and an incentive fee of 20% of profits
- Liquidity: Often have lock-up periods, require advance redemption notices, or may be gated

Mutual Fund

- Compensation structure: Fees are usually a fixed percentage of assets
- Liquidity: Can move more easily into and out of a mutual fund



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Hedge Fund Strategies

- Directional
 - Bets that one sector or another will outperform other sectors
- Non-directional
 - Exploit temporary misalignments in relative valuation across securities
 - Buy one type of security and sell another
 - Market neutral
- Implications for Beta of each strategy?



Directional Trading

- In contrast to non-directional, market-neutral strategies, directional funds make large sectoral bets
- Examples: Global Macro funds (e.g. Soros' Quantum Hedge Fund) make large macro bets on currencies, commodities, sectors.



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Non-Directional Trading

- Relative value identifies rich vs. cheap based on a model of what prices “should be”
 - Sometimes, economic models (e.g. Royal Dutch/Shell)
 - Often, statistical models
- Statistical Arbitrage
 - Use data mining techniques to uncover systematic pricing patterns
 - Trade on divergence from normal
 - Can involve high frequency trading over short holding periods



Statistical Arbitrage Example: Pairs Trading

- Find stocks which move together
 - For a given pair, the relative value (p_1/p_2) provide a buy/sell signal
 - High p_1/p_2 implies buy stock 2 and short stock 1
- David Shaw (D.E. Shaw) argues “...human beings don’t like to trade against human nature, which wants to buy stocks after they go up, not down.”
- Long-short strategy is self-financing and market neutral



Pairs Trading Cookbook

Step A: find stocks which move together

1. For each stock, subtract off mean price, divide by standard deviation (normalized prices),

$$\tilde{p} = \frac{p - \bar{p}}{\sigma_p}$$

2. Calculate sum of squared deviations of normalized prices $\sum (p_1 - p_2)^2$ across all possible pairs of stocks $(N(N-1)/2)$

3. Each stock is paired with the stock for which the sum of squared errors is smallest

What is implication for paired stocks β ?

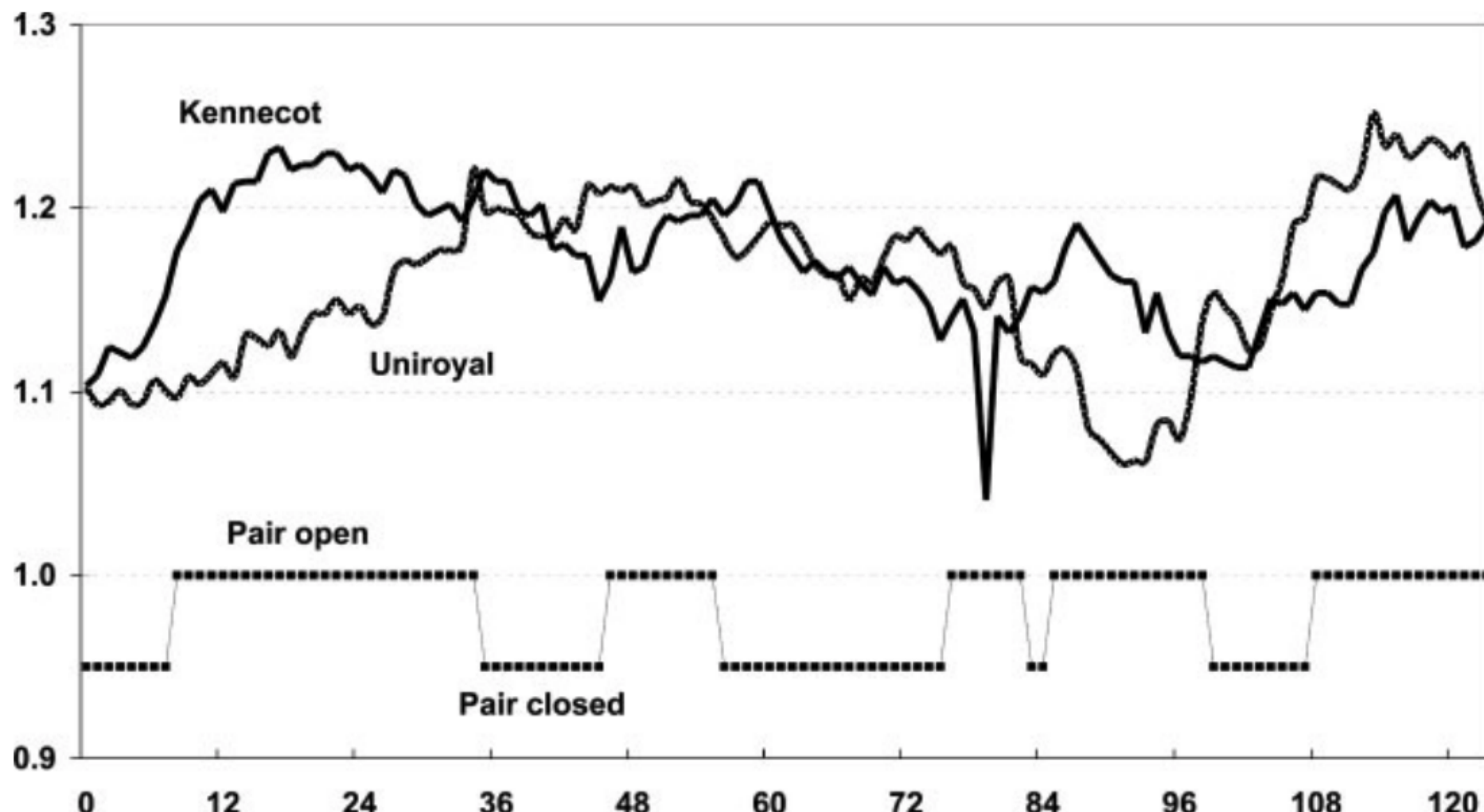
Pairs Trading Cookbook

- Limit focus to “top pairs”
 - Chose top 5% pairs based on minimum sum of squared deviations
- Devise trading rule
 1. Define daily distance as $d = (\tilde{p}_1 - \tilde{p}_2)^2$ and calculate historical standard deviation of price differences
 2. “Open” pair when $d > 2\sigma(d)$
 3. “Close” pair when $d = 0$



Pairs Trading Cookbook

Goetzmann, Gatev and Rouwenhorst (2006)



Pairs Trading Results

Excess returns of unrestricted pairs trading strategies

Pairs portfolio	Top 5	Top 20
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A. Excess return distribution (no waiting)		
Average excess return (fully invested)	0.01308	0.01436
Standard error (Newey-West)	0.00148	0.00124
<i>t</i> -Statistic	8.84	11.56
Excess return distribution		
Median	0.01194	0.01235
Standard deviation	0.02280	0.01688
Skewness	0.62	1.39
Kurtosis	7.81	10.54
Minimum	−0.10573	−0.06629
Maximum	0.14716	0.13295
Observations with excess return < 0	26%	15%
Average excess return on committed capital	0.00784	0.00805

Pairs Trading Results

- Does pairs trading expose trade to risk factors?
- Market neutrality suggests CAPM alpha, but what about other risks?

Factor model: Fama–French, Momentum,
Reversal

Intercept	0.00545 (3.81)
Market	−0.06661 (−1.03)
SMB	−0.04233 (−0.71)
HML	0.05740 (1.37)
Momentum	−0.02804 (−0.94)
Reversal	0.10192 (1.50)
R^2	0.05

- Coefficients and t-statistics from a five-factor model

Merger Arbitrage

- Often a long-short strategy which buys target and sells acquirer in announced mergers
- Hedge fund holds event risk
 - Terms not reached
 - Alternate bidders
 - Regulatory approval not granted



Merger Arbitrage Example

- Tellabs and Ciena merger
 - Both companies involved in fiber-optic/telecom networks
 - Merged company would be able to compete with larger firms such as Lucent by sharing customer bases, exploiting size
- 1-for-1 stock swap announced June 3, 1998
 - Tellabs \$64/share
 - Ciena \$60/share
 - Upon merger, prices must be equal



Merger Arbitrage Example

- Another infamous LTCM trade
 - Commit \$30M own capital, Borrow \$30M @ 6% prime rate
 - Buy 1M Ciena @ \$60
 - Sell 1M Tellabs @ \$64
 - Earn 4.5% short rebate (interest) on proceeds from short
- What happens?
 - Ciena loses two key customers, shares fall to \$15 dollars, deal is abandoned
 - Tellabs shares also decline before position is closed



Merger Arbitrage Example

- Profits and losses from trade:
 - $\$30\text{M} @ 6\% \text{ prime rate} \times (110/360) = -\550K
 - $\$64\text{M short rebate} @ 4.5\% \times (110/360) = \880K
 - $\text{Loss on Ciena } 1\text{M} \times (\$15 - \$60) = -\45M
 - $\text{Gain on Tellabs } -1\text{M} \times (\$64 - \$42) = \22M
 - $\text{TOTAL} = -\$22.7\text{M}$

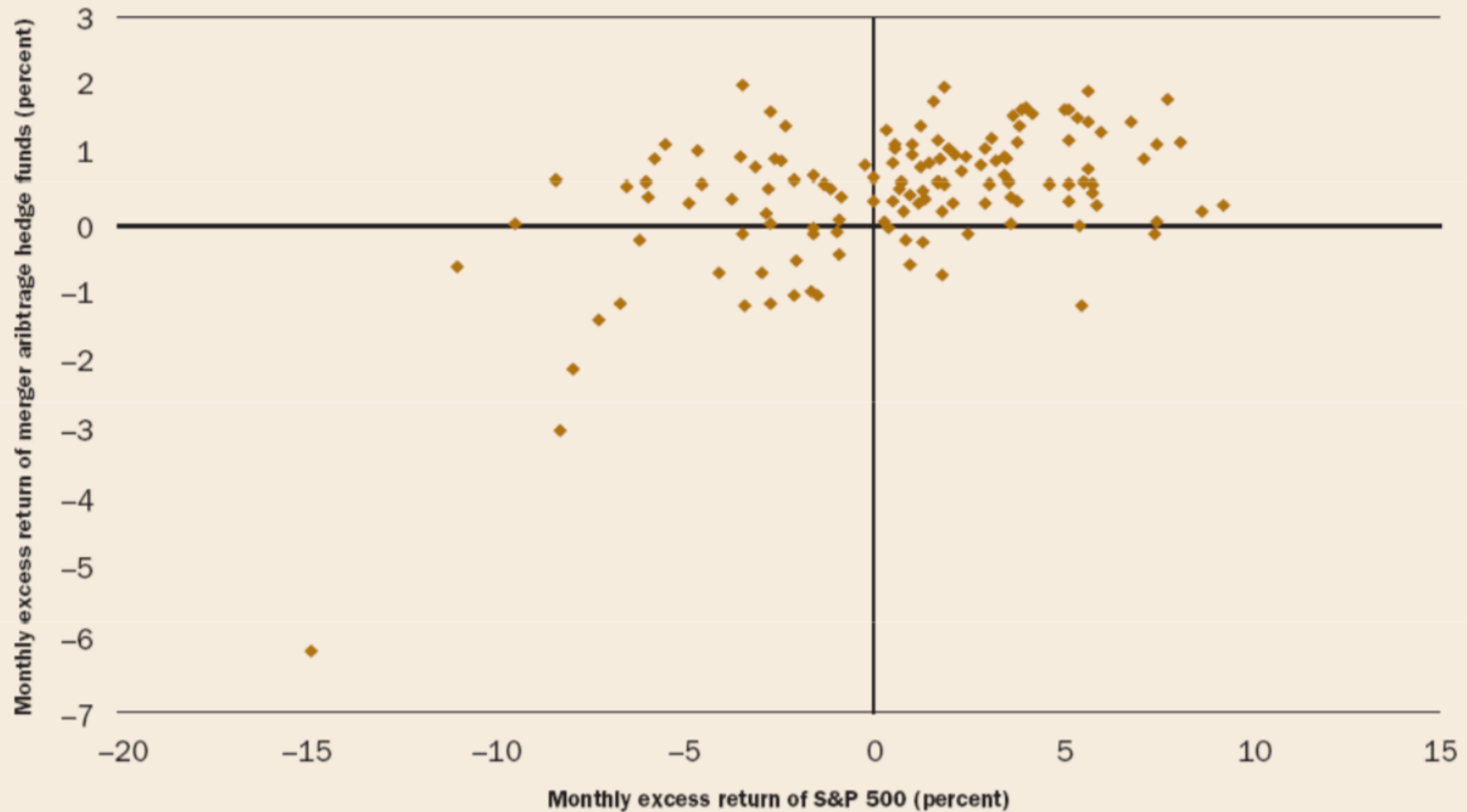
Total return on committed capital: -75.57%



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Merger Arbitrage: large sample evidence

Risk Factor for Merger Arbitrage Hedge Funds, 1994–2004



Source: HFR, Datastream

Merger Arbitrage: large sample evidence

- Merger arb is profitable on average
 - Theory: hedge funds earn premium for insuring shareholders against completion risk

		Intercept		$R_{Mt} - R_f$		SMB		HML		
	N	R^2	a	p -value	b	p -value	s	p -value	h	p -value
<hr/>										
<i>Panel B: First offers</i>										
Value-weighted										
Market model	192	0.15	0.86	(0.00)	0.32	(0.04)				
Fama-French three-factor	192	0.20	0.72	(0.02)	0.37	(0.02)	0.31	(0.04)	0.25	(0.07)
Equal-weighted										
Market model	192	0.12	0.80	(0.00)	0.22	(0.00)				
Fama-French three-factor	192	0.16	0.73	(0.00)	0.24	(0.00)	0.23	(0.01)	0.15	(0.11)

- 72–86 bps in monthly alpha!

Hedge Fund Performance Evaluation

- Recall our CAPM-based single factor model

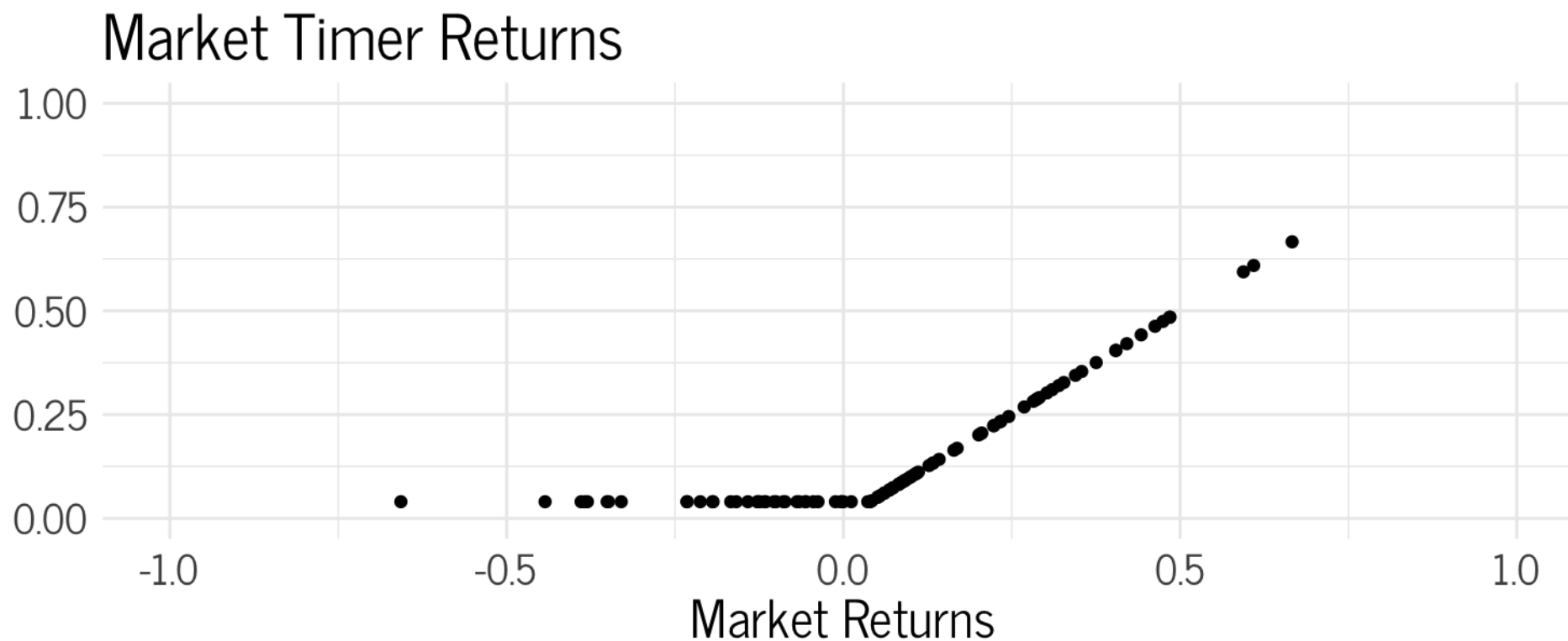
$$r_{i,t} - r_f = \alpha_i + \beta_i(r_{m,t} - r_f) + e_{i,t}$$

- Note that for hedge funds, factor loadings are *dynamic*
 - Consider market loading for a long-only market timer
 - If successful, β is only positive when market returns are high
 - Implies non-linear factor loadings



Dynamic Performance Evaluation

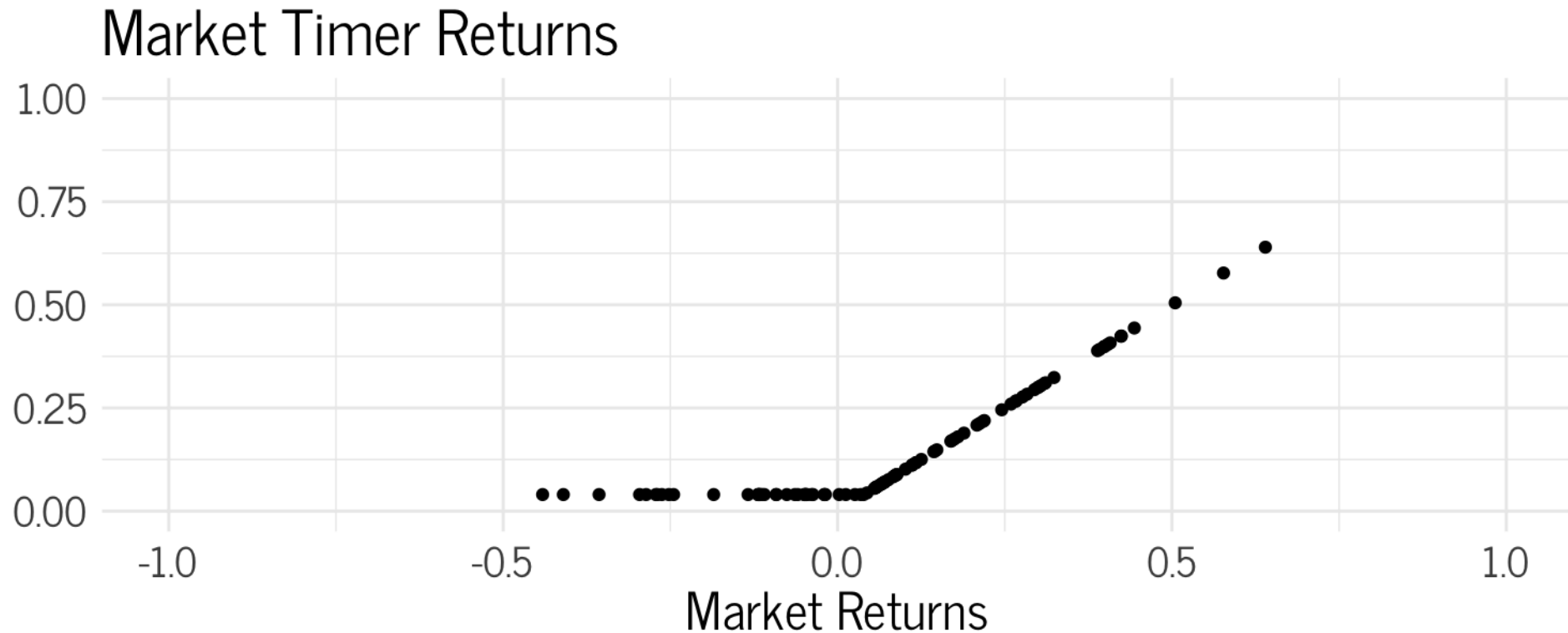
- Suppose with perfect foresight, we can
 1. Buy market when above risk-free rate of 4%
 2. Hold t-bills when market returns below r_f



Dynamic Performance Evaluation

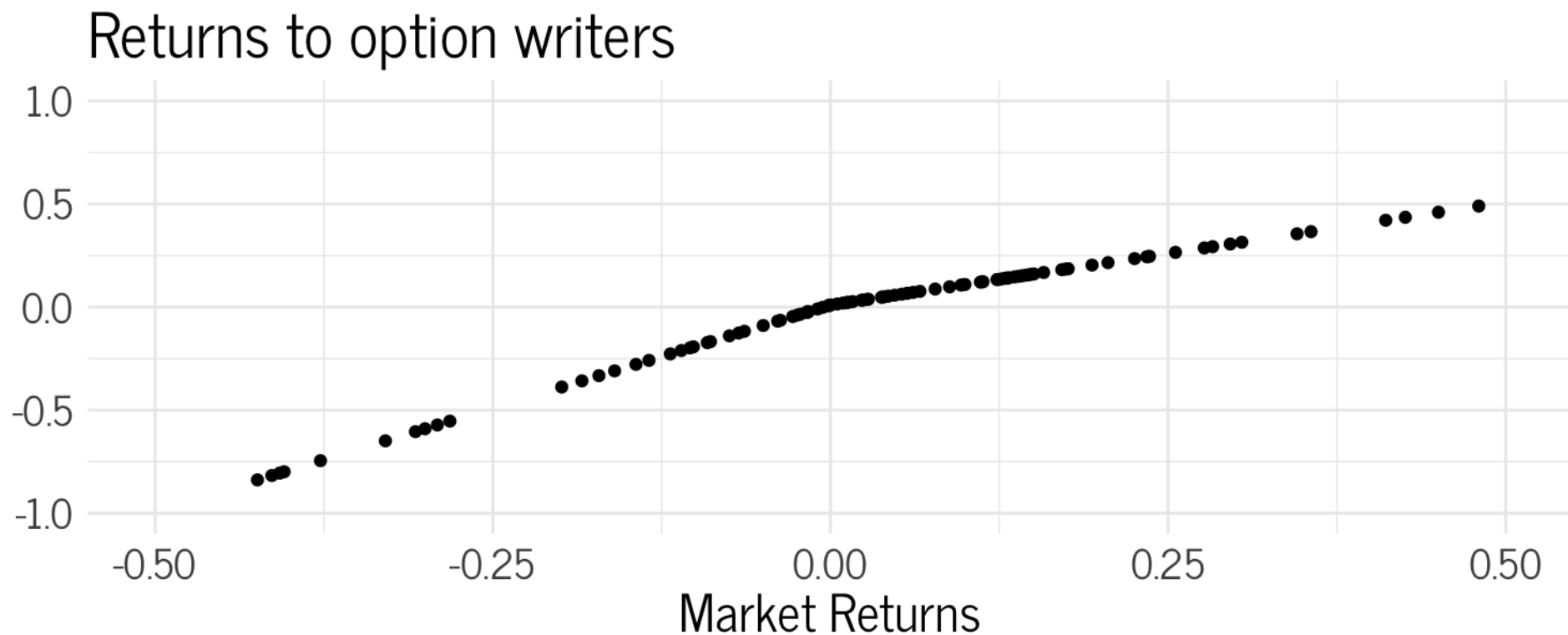
$$r_p = \alpha + r_f + \beta_1(r_m - r_f) + \beta_2(r_m - r_f)^2 + \epsilon_p$$

- $\beta_2 > 0$ implies market timing ability



Dynamic Performance Evaluation

- Alternatively, hedge funds may write out of the money put options that exacerbate downturns



Dynamic Performance Evaluation

$$r_p = \alpha + r_f + \beta_1(r_m - r_f) + \beta_2(r_m - r_f)^2 + \epsilon_p$$

- $\beta_2 < 0$ may imply option writing



Non-linear loadings across asset classes

$$\tilde{r}_{p,t}^e = \alpha_p + \beta^+ \max\{\tilde{r}_{m,t}^e, 0\} + \beta^- \min\{\tilde{r}_{m,t}^e, 0\} + \epsilon_{p,t}$$

Non-linear market loadings

