Topic 2: Behavioral Anomalies

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SAFE PhD Course on Anomalies – June, 2024

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Behavioral finance

- Definition (Barberis and Thaler, 2003):

  Behavioral finance argues that some financial phenomena can plausibly be understood using models in which some agents are not fully rational.

- Building blocks
  - Limits to arbitrage – it can be difficult for rational traders to undo the dislocations caused by irrational traders
  - Psychology – catalogues the kinds of deviations from full rationality we might expect to see

Behavioral finance: Cross-section of stock returns

- Overreaction studies
  - Long-run reversals (De Bondt and Thaler, 1985)
  - Short-run reversals (Jegadeesh, 1990)

- Underreaction studies
  - Post-earnings announcement drift (Foster, Olsen, and Shevlin, 1984; Bernard and Thomas, 1989; Chan, Jegadeesh, and Lakonishok, 1996)
  - Momentum (Jegadeesh and Titman, 1993; Asness, 1994; Moskowitz and Grinblatt, 2001)
  - Countless slow diffusion of information studies (e.g., Cohen and Frazzini, 2008; Cohen, Malloy, and Frazzini, 2010)

De Bondt and Thaler (1985): Overview

- Sort stocks on their prior three year cumulative return
- Form a winner portfolio of the 35 stocks with best prior record and a loser portfolio of the 35 stocks with worst prior record
- Look at performance of both portfolios over the next three years
  - Rebalance every three years

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De Bondt and Thaler (1985): Result

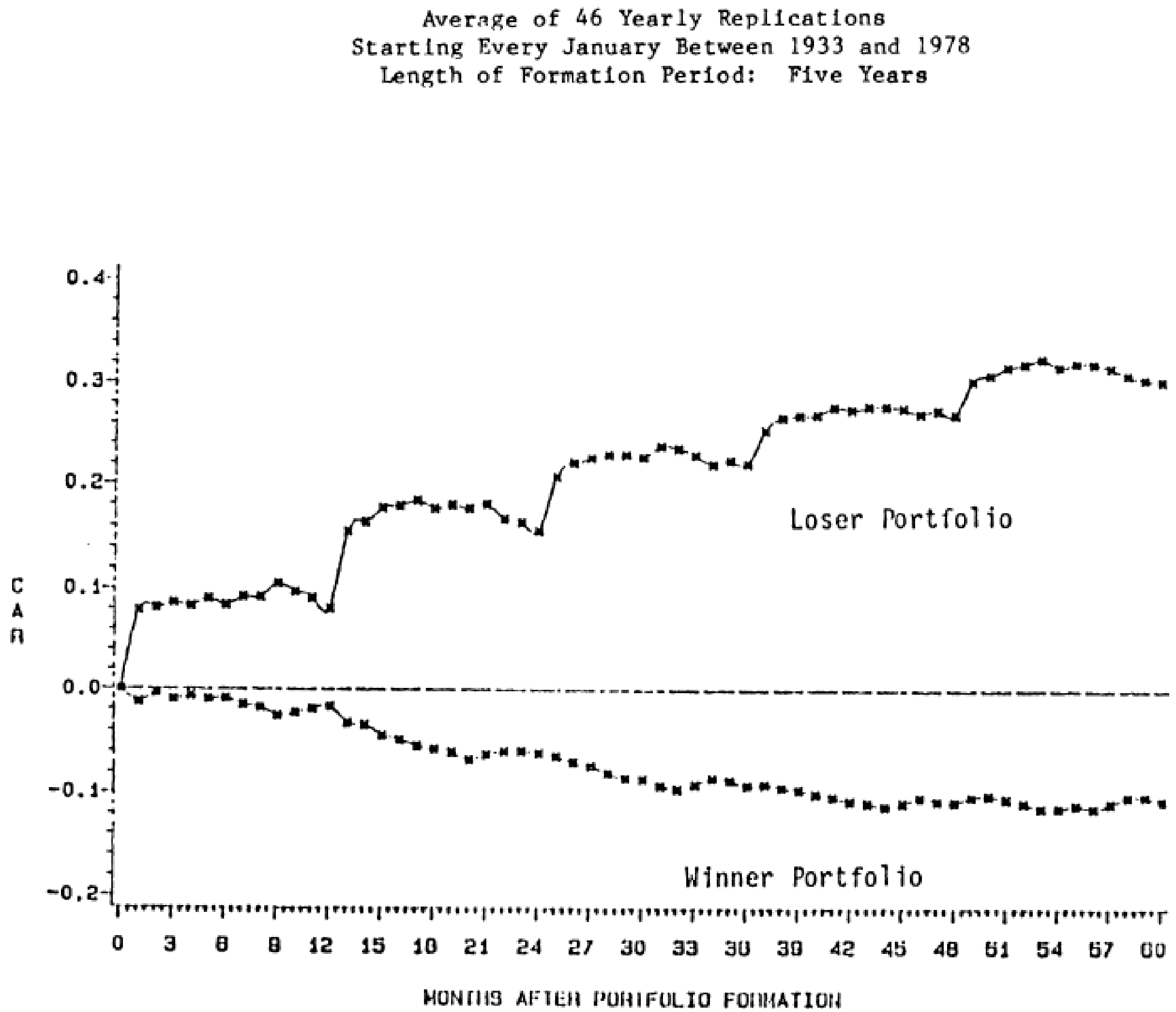

Figure 3. Cumulative Average Residuals for Winner and Loser Portfolios of 35 Stocks (1–60 months into the test period)

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De Bondt and Thaler (1985): Controversy

- From Barberis and Thaler (2003):

When De Bondt and Thaler's (1985) paper was published, many scholars thought that the best explanation for their findings was a programming error. Since then their results have been replicated numerous times by authors both sympathetic to their view and by those with alternative views. At this stage, we think that most of the empirical facts are agreed upon by most of the profession, although the interpretation of those facts is still in dispute. This is progress. If we all agree that the planets do orbit the sun, we can focus on understanding why.

De Bondt and Thaler (1985): Resolution

- The result that sold the Fama and French (1993) 3-factor model
- The long-run reversal effect was completely subsumed by the FF93 factors

Table VII

Three-Factor Regressions for Monthly Excess Returns (in Percent) on Equal-Weight NYSE Portfolios Formed on Past Returns: 7/63–12/93, 366 Months

$$R_i - R_f = a_i + b_i(R_M - R_f) + s_i\text{SMB} + h_i\text{HML} + \varepsilon_i$$

The formation of the past-return deciles is described in Table VI. Decile 1 contains the NYSE stocks with the lowest continuously compounded returns during the portfolio-formation period (12-2, 48-2, or 60-13 months before the return month). $t()$ is a regression coefficient divided by its standard error. The regression R^2s are adjusted for degrees of freedom. GRS is the F-statistic of Gibbons, Ross, and Shanken (1989), testing the hypothesis that the regression intercepts for a set of ten portfolios are all 0.0. p(GRS) is the p-value of GRS.

	1	2	3	4	5	6	7	8	9	10	GRS	p(GRS)
Portfolio formation months are t-12 to t-2												
a	−1.15	−0.39	−0.21	−0.22	−0.04	−0.05	0.12	0.21	0.33	0.59		
b	1.14	1.06	1.04	1.02	1.02	1.02	1.04	1.03	1.10	1.13		
s	1.35	0.77	0.66	0.59	0.53	0.48	0.47	0.45	0.51	0.68		
h	0.54	0.35	0.35	0.33	0.32	0.30	0.29	0.23	0.23	0.04		
$t(a)$	−5.34	−3.05	−2.05	−2.81	−0.54	−0.93	1.94	3.08	3.88	4.56	4.45	0.000
$t(b)$	21.31	33.36	42.03	51.48	61.03	73.62	68.96	62.67	51.75	35.25		
$t(s)$	17.64	16.96	18.59	20.87	22.06	23.96	21.53	19.03	16.89	14.84		
$t(h)$	6.21	6.72	8.74	10.18	11.86	13.16	11.88	8.50	6.68	0.70		
R^2	0.75	0.85	0.89	0.92	0.94	0.96	0.95	0.94	0.92	0.86		
Portfolio formation months are t-48 to t-2												
a	−0.73	−0.32	−0.09	−0.08	−0.05	−0.00	0.07	0.10	0.15	0.37		
b	1.16	1.12	1.06	1.05	1.02	1.01	1.00	0.99	1.04	1.11		
s	1.59	0.87	0.64	0.52	0.48	0.42	0.41	0.40	0.42	0.49		
h	0.90	0.60	0.44	0.44	0.36	0.31	0.18	0.11	−0.05	−0.26		
$t(a)$	−2.91	−2.79	−0.96	−0.99	−0.67	−0.01	1.08	1.46	2.09	3.60	2.02	0.031
$t(b)$	18.61	39.22	46.55	53.19	57.82	63.78	64.72	58.62	57.02	43.37		
$t(s)$	17.91	21.36	19.68	18.61	19.17	18.51	18.52	16.61	16.22	13.40		
$t(h)$	8.91	12.94	11.93	13.78	12.61	11.87	7.34	4.19	−1.55	−6.35		
R^2	0.73	0.88	0.91	0.92	0.93	0.94	0.95	0.93	0.94	0.90		
Portfolio formation months are t-60 to t-13												
a	−0.18	−0.16	−0.13	−0.07	0.00	0.02	0.06	0.10	−0.07	−0.12		
b	1.13	1.09	1.07	1.04	0.99	1.00	1.00	1.01	1.06	1.15		
s	1.50	0.83	0.67	0.59	0.47	0.38	0.35	0.40	0.45	0.50		
h	0.87	0.54	0.50	0.42	0.34	0.29	0.23	0.13	−0.00	−0.26		
$t(a)$	−0.80	−1.64	−1.69	−0.99	0.02	0.40	0.96	1.43	−0.92	−1.36	1.29	0.235
$t(b)$	20.24	44.40	55.03	61.09	63.79	65.68	62.58	58.26	60.49	53.04		
$t(s)$	18.77	23.63	24.09	24.06	21.21	17.44	15.43	16.18	18.06	16.33		
$t(h)$	9.59	13.67	15.94	15.31	13.46	11.82	8.98	4.46	−0.14	−7.50		
R^2	0.75	0.91	0.93	0.94	0.94	0.94	0.94	0.93	0.94	0.93		

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Short-run reversals

- Jegadeesh (1990) and Lehman (1990)
  - Losers over the past one week to one month outperform winners over the next one week to one month
  - Significant profits – up to 2%/month

- Both behavioral and microstructure explanations
  - Overreaction to information, fads, cognitive errors
    - Lehman (1990)
  - Bid-ask bounce
    - Lo and MacKinlay (1990), Jegadeesh and Titman (1995)

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Momentum

- Jegadeesh and Titman (1993)
  - Stocks that perform best (worst) over a three- to 12-month period tend to continue to perform well (poorly) over the subsequent three- to 12-months
  - Improvement when skipping the last week to avoid short-term reversals

- Momentum strategies profitable in most major markets around the world (Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003; Chui, Titman, and Wei, 2010)
  - Japan a notable exception!

- And in other asset classes (Asness, Moskowitz, and Pedersen, 2013)

Momentum refinements

- In the cross-section, momentum is stronger with:
  - Small caps & less analysts (Hong, Lim, and Stein, 2000)
  - Growth stocks (Daniel and Titman, 1999)
  - Information uncertainty (Zhang, 2006; Sagi and Seasholes, 2007)
  - Higher turnover (Lee and Swaminathan, 2000)
  - Low credit ratings (Avramov et al., 2007)
  - Cultural differences across countries (Chui et al., 2010)

- In the time-series, momentum is stronger in:
  - Economic expansions (Chorida and Shivakumar, 2002)
    - Although questioned later (Griffin et al., 2003; Cooper et al., 2004)
  - High market volatility (Stivers and Sun, 2010; Wang and Xu, 2010)
  - High investor sentiment (Antoniu et al., 2010)

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Momentum refinements/variations

- Intermediate- vs recent-past returns (Novy-Marx, 2012)
    - Effect is more akin to an "echo"
    - Explains momentum

- Industry momentum (Moskowitz and Grinblatt, 1999)
    - Not quite the same thing
    - Works pretty well when sorting by last month's industry return, regardless of the industry classification

- Earnings momentum
    - Huge literature in accounting, kind of independent for a long time

Earnings (aka fundamental) momentum

- Momentum in earnings announcements
  - Jones & Litzenberger (1970), Latane & Jones (1979), Givoly and Lakonishok (1979), Foster et al. (1984), Bernard & Thomas (1989), Chan et al. (1996), Brandt et al. (2008)
  - Sort stocks based on a "standardized unexpected earnings" (SUE) measure:

$$SUE = \frac{Quarterly\ earnings\ -Expected\ quarterly\ earnings}{Standard\ deviation\ of\ quarterly\ earnings}$$

- Some evidence it exists in other asset classes too (Brooks, 2017)

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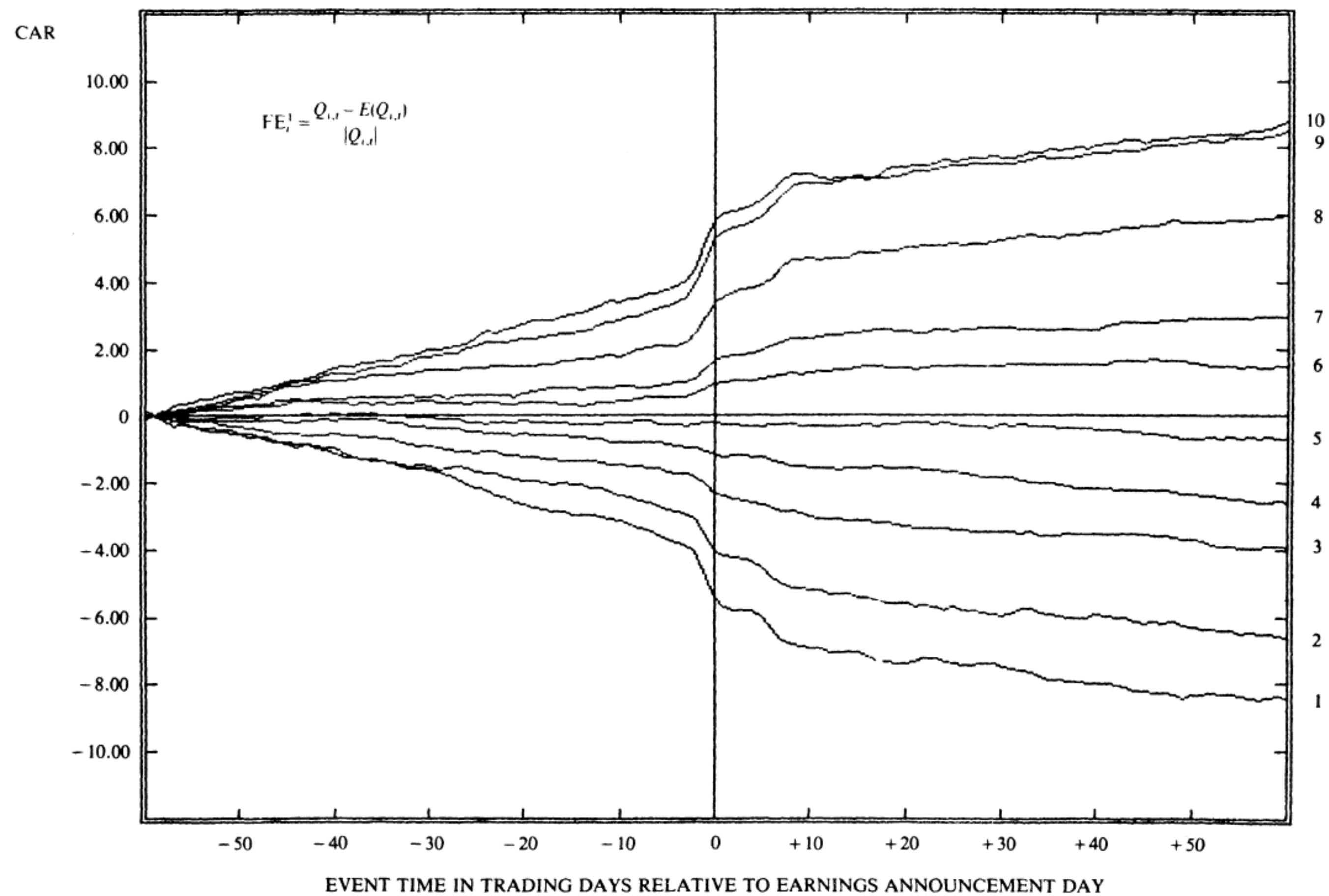
Earnings (aka fundamental) momentum

- Foster, Olsen, and Shevlin (1984):



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Price vs Earnings momentum

- Early evidence (Chan et al., 1996; 2000) concluded they are independent

- More recent evidence, however, concludes price momentum is a manifestation of earnings momentum
  - Chordia and Shivakumar (2006) find that "the price momentum anomaly is a manifestation of the earnings momentum anomaly"
  - Novy-Marx (2018) finds similar evidence

- It's also why Lu Zhang's ROE factor helps in pricing momentum portfolios (Novy-Marx, 2015)

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Slow diffusion of information studies

- More papers than I can count produce anomaly signals by finding a piece of stock-related information that is difficult to process for investors

- Classic examples (both won Smith-Breeden @ JF)
  - Cohen and Frazzini (2008)
    - Stock prices do not promptly incorporate news about economically related firms, generating return predictability across asset
  - Cohen, Frazzini, Malloy (2010)
    - Analysts outperform by up to 6.60% per year on their stock recommendations when they have an educational link to the company.

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Slow diffusion of information studies

- Partial list of empirical studies
  - Lo and MacKinlay (1990): Small caps respond more slowly to market-wide news
  - Hou (2007): large caps returns predict small cap returns within industry
  - Cohen and Frazzini (2008): customer stock returns predict supplier stock returns
  - Frazzini and Lamont (2008): fund flows (dumb money) negatively predicts stock returns
  - Menzly and Ozbas (2010): customer and customer industries cross-predict each others' returns
  - Cohen and Lou (2012): single-industry stock returns predict conglomerate stock returns
  - Cohen, Malloy, and Pomorski (2012): publicly-reported non-routine trades by insiders predict returns
  - Korniotis and Kumar (2013): Firms' locations states' macro conditions predict returns
  - Cohen, Diether, and Malloy (2013): R&D track record predicts returns
  - Cohen, Diether, and Malloy (2013): "interested" legislator behavior predicts returns
  - Parsons, Sabatucci, and Titman (2020): coheadquarted firms predict each others' stock returns
  - Moore and Velikov (2022): past earnings sensitivity to oil price changes predicts stock returns

- Some theoretical justification
  - Hirshleifer and Teoh (2003) emphasizes how the information's presentation and timing chosen by firms can affect investor's abilities to process disclosures
  - Hirshleifer, Lim, and Teoh (2011) develop a model in which investors with limited attention can explain the delayed reaction

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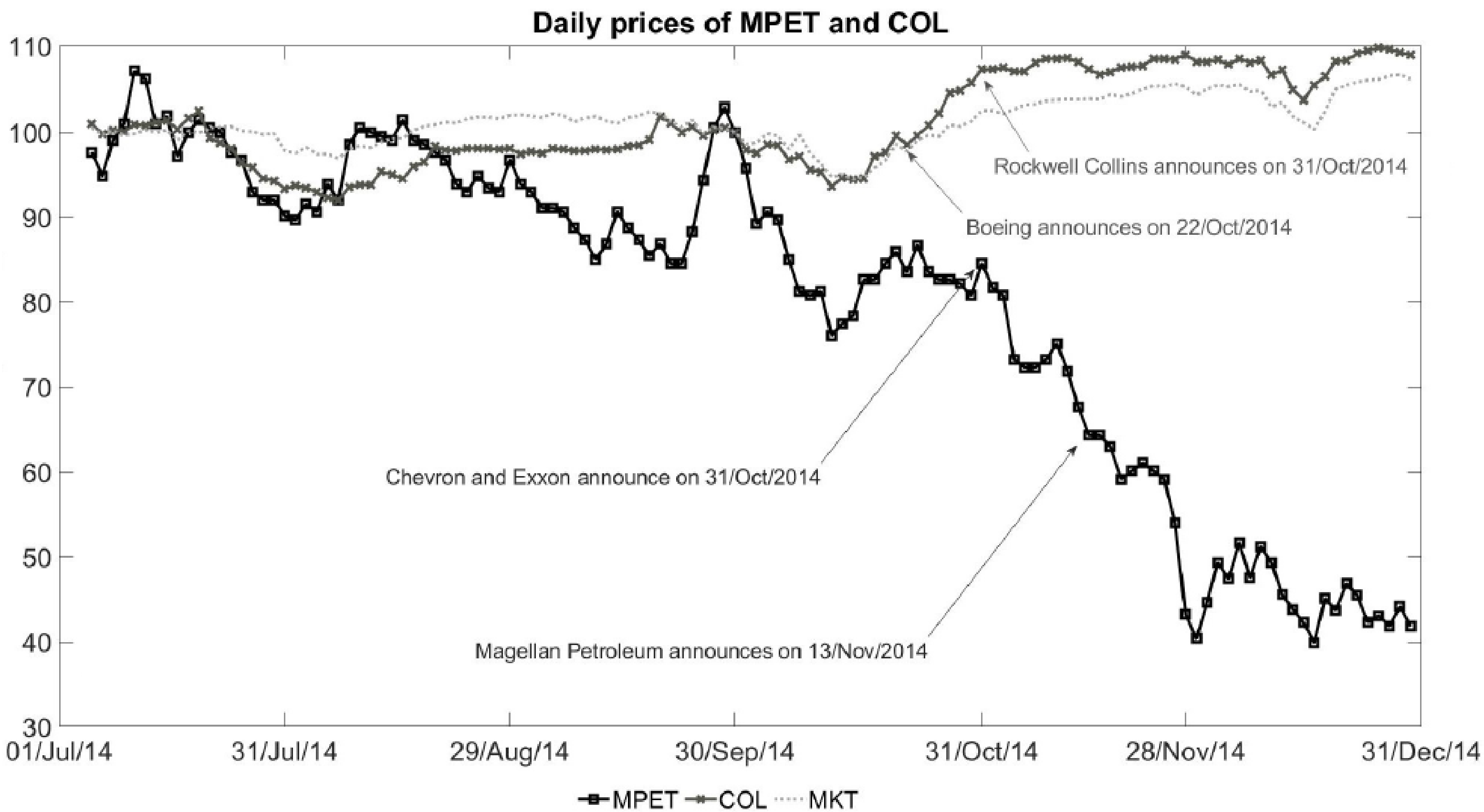
Moore and Velikov (RAPS, 2024)

Figure 1: Example Long and Short Positions
This figure plots the stock prices of Rockwell Collins (ticker=COL) and Magellan Petroleum (ticker=MPET) between July 2014 and December 2014. Our strategy takes a long position in COL and a short position in MPET from September 30, 2014 until December 31, 2014. The thin solid line shows the performance of COL, the thick solid line shows the performance of MPET, and the dotted line shows the performance of the market portfolio. Prices are normalized so that the price of both stocks and the market portfolio is 100 on September 30, 2014. The figure indicates when COL, MPET, and the largest firms in their industries announce earnings.



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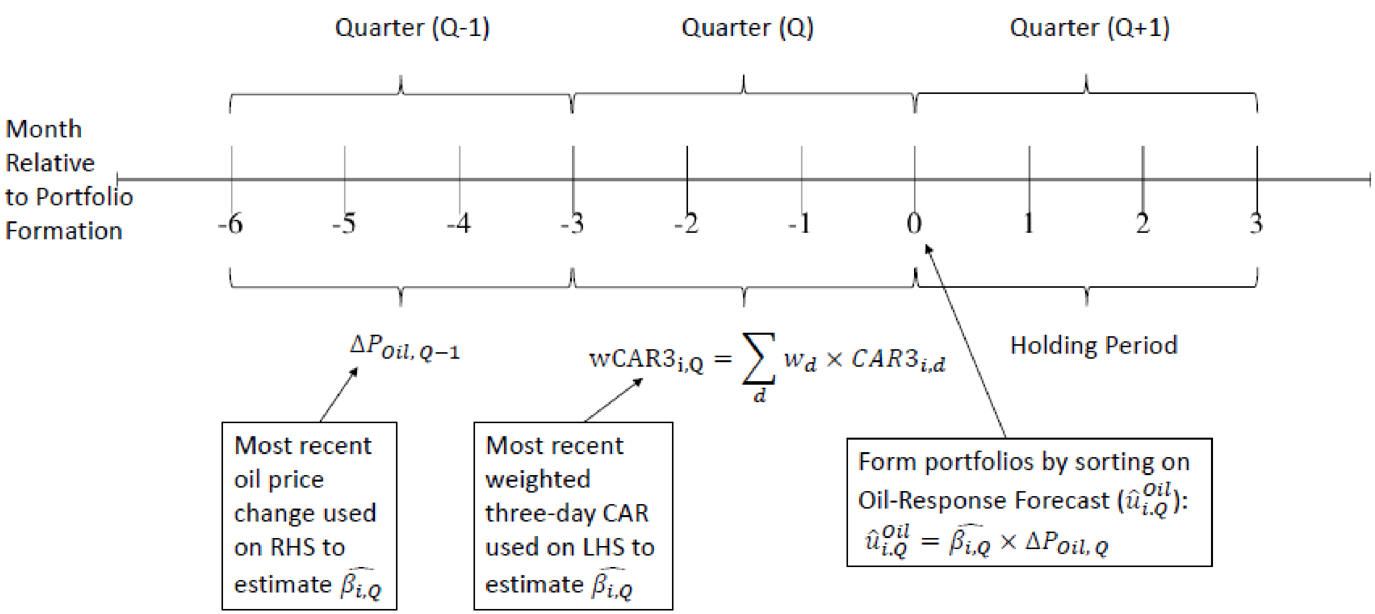
Moore and Velikov (RAPS, 2024)

Figure 2: Estimating Oil Price Exposure and Oil-Response Forecast

This figure illustrates the procedure for estimating oil price exposure and oil-response forecast. These are the second and third steps in our three-step procedure for estimating each stock's quarterly oil-response forecast, the sorting variable in our trading strategy. At the end of each quarter, Q, for each stock, i, we estimate oil price exposure, $\hat{\beta}_{i,Q}$ from: $wCAR3_{i,t} = \alpha_{i,Q} + \beta_{i,Q}\Delta P_{Oil,t-1} + \varepsilon_{i,t}$, where $t \in [Q-11, Q]$. The dependent variable, $wCAR3_{i,t}$ is the stock's industry-weighted CAR3 in quarter t. Figure 3 provides an example of how we calculate industry-weighted CAR3 for a single quarter. The most recent value of the dependent variable is from quarter Q. The independent variables include an intercept and the oil price change from the calendar quarter prior to the quarterly industry-weighted CAR3. The most recent value of the independent variable is the oil price change in quarter $Q-1$. The oil price is the USD price per barrel of West Texas Intermediate. The oil-response forecast (Equation 1) at the end of quarter Q is the product of the stock's oil price exposure at the end of quarter Q and the oil price change in quarter Q. We use the oil-response forecast at the end of quarter Q to form portfolios, and we hold these portfolios during quarter $Q+1$.



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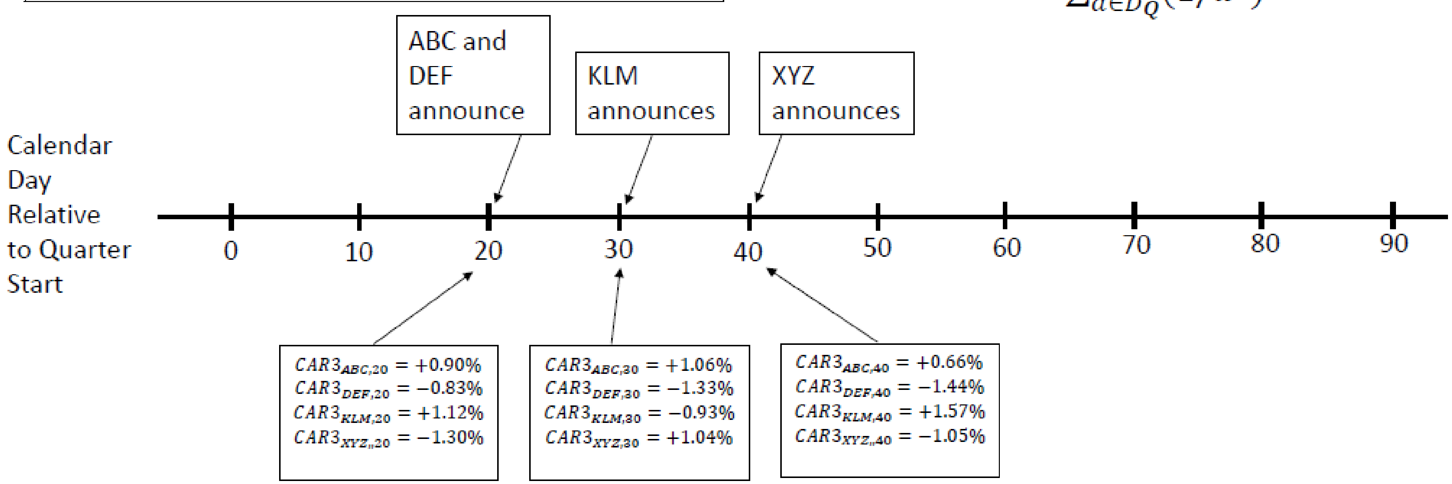
Moore and Velikov (RAPS, 2024)

Figure 3: Estimating Industry-Weighted CAR3.
At the end of each quarter, we calculate each stock's industry-weighted CAR3 (wCAR3). This is the first step in our three-step procedure for estimating each stock's quarterly oil-response forecast, the sorting variable in our trading strategy. The cumulative abnormal return (CAR3) is the stock return in excess of the market return in the three-day window centered around the stock's earnings announcement date. In this example, we consider a Sample industry with four stocks: ABC, DEF, KLM, and XYZ. Each stock announces earnings on a particular day, which is d calendar days after the end of the previous quarter. We calculate each stock's CAR3 on every day that any firm in the same industry announces earnings. Each stock's wCAR3 is a weighted average of its own CAR3 on the days that any firm in the same industry announces earnings. The weighting function uses $1/d^2$ for each firm's earnings announcement, which places more weight on a firm's CAR3 when other firms in the firm's industry announce earnings early in the quarterly earnings season.

Industry	Stock	Ann. Date	Days in Q	wCAR3
Sample	ABC	January 20	20	+0.91%
Sample	DEF	January 20	20	-1.05%
Sample	KLM	January 30	30	+0.65%
Sample	XYZ	February 9	40	-0.65%

$$wCAR3_{i,Q} = \sum_{d \in D_Q} w_d \times CAR3_{i,d}$$

$$w_d = \frac{1/d^2}{\sum_{d \in D_Q}(1/d^2)}$$



Moore and Velikov (RAPS, 2024)

Table 2: Time-Series Regressions

This table reports average excess returns, alphas, and Fama and French (2015) five-factor model loadings for portfolios sorted on oil-response forecast. At the end of each quarter, we sort stocks into five portfolios based on their oil-response forecast using NYSE breakpoints. Equation 1 shows how to calculate oil-response forecast. Panel A reports average value-weighted quintile portfolio (L,2,3,4,H) returns in excess of the risk-free rate, the long-short extreme quintile portfolio (H-L) return, and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, and Fama and French (2015) five-factor model. Panel B reports the factor loadings for the quintile portfolios and long-short extreme quintile portfolio in the Fama and French (2015) five-factor model. T-statistics are in brackets. The sample period is 01/1975 to 12/2021.

Panel A: Excess returns and alphas on oil-response forecast-sorted portfolios

	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.58	0.62	0.60	0.75	1.00	0.42
	[2.64]	[3.48]	[3.60]	[4.33]	[4.61]	[3.44]
α^{CAPM}	-0.22	-0.03	-0.01	0.12	0.22	0.44
	[-2.41]	[-0.39]	[-0.17]	[1.58]	[2.21]	[3.57]
α^{FF3}	-0.24	-0.04	-0.03	0.10	0.19	0.43
	[-2.56]	[-0.52]	[-0.49]	[1.44]	[1.94]	[3.46]
$\alpha^{\text{FF3+UMD}}$	-0.19	-0.05	-0.03	0.15	0.31	0.51
	[-2.04]	[-0.64]	[-0.48]	[2.17]	[3.23]	[4.03]
α^{FF5}	-0.17	-0.12	-0.12	0.02	0.31	0.47
	[-1.74]	[-1.54]	[-1.78]	[0.29]	[3.01]	[3.66]

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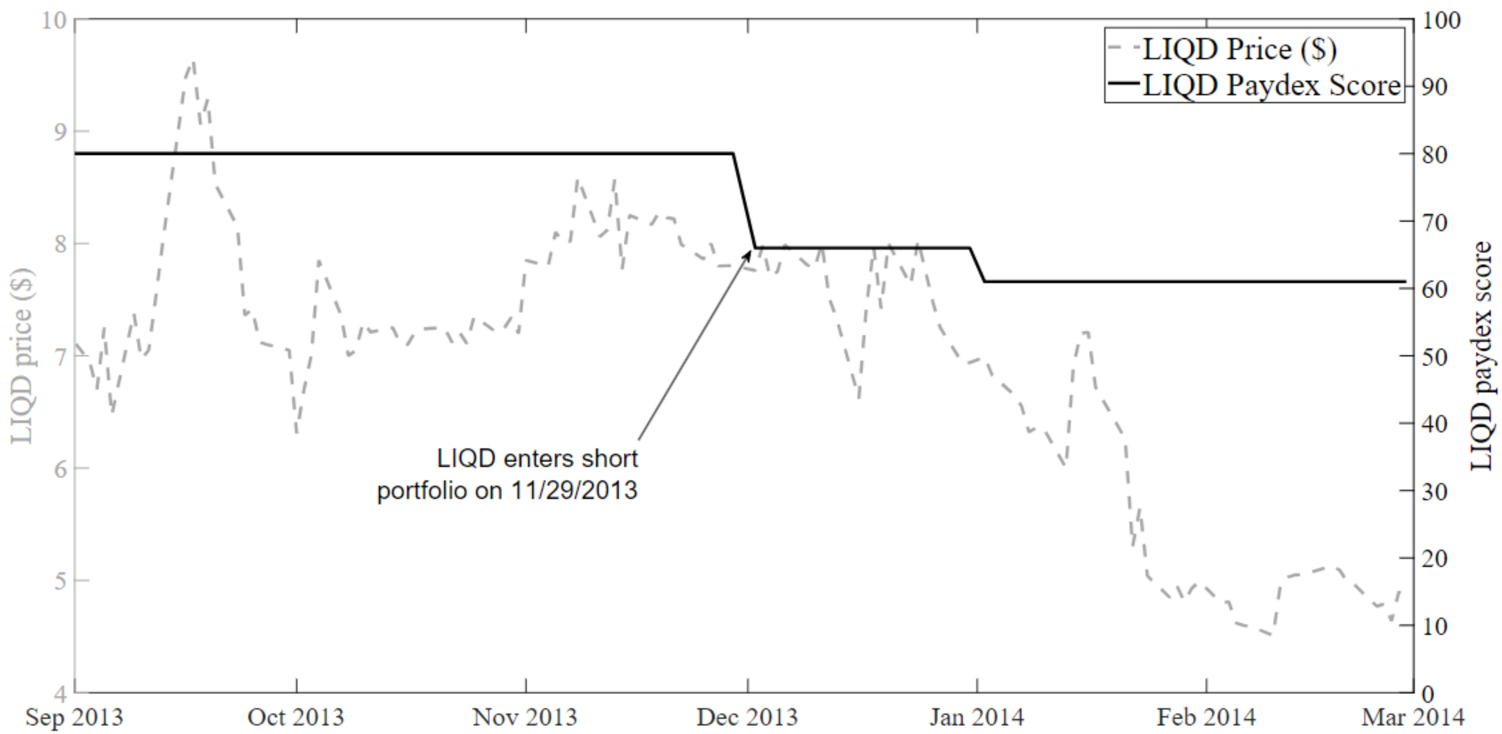
Lieberman et al. (JFE, R&R)

Figure 1: Stock price and PAYDEX score for Liquid Holdings Group, Inc.
The figure plots the daily stock price (left scale) and PAYDEX score (right scale) for Liquid Holdings Group, Inc. (LIQD) between September 2013 and March 2014. LIQD announced earnings on 10/31/2013 and 2/27/2014.



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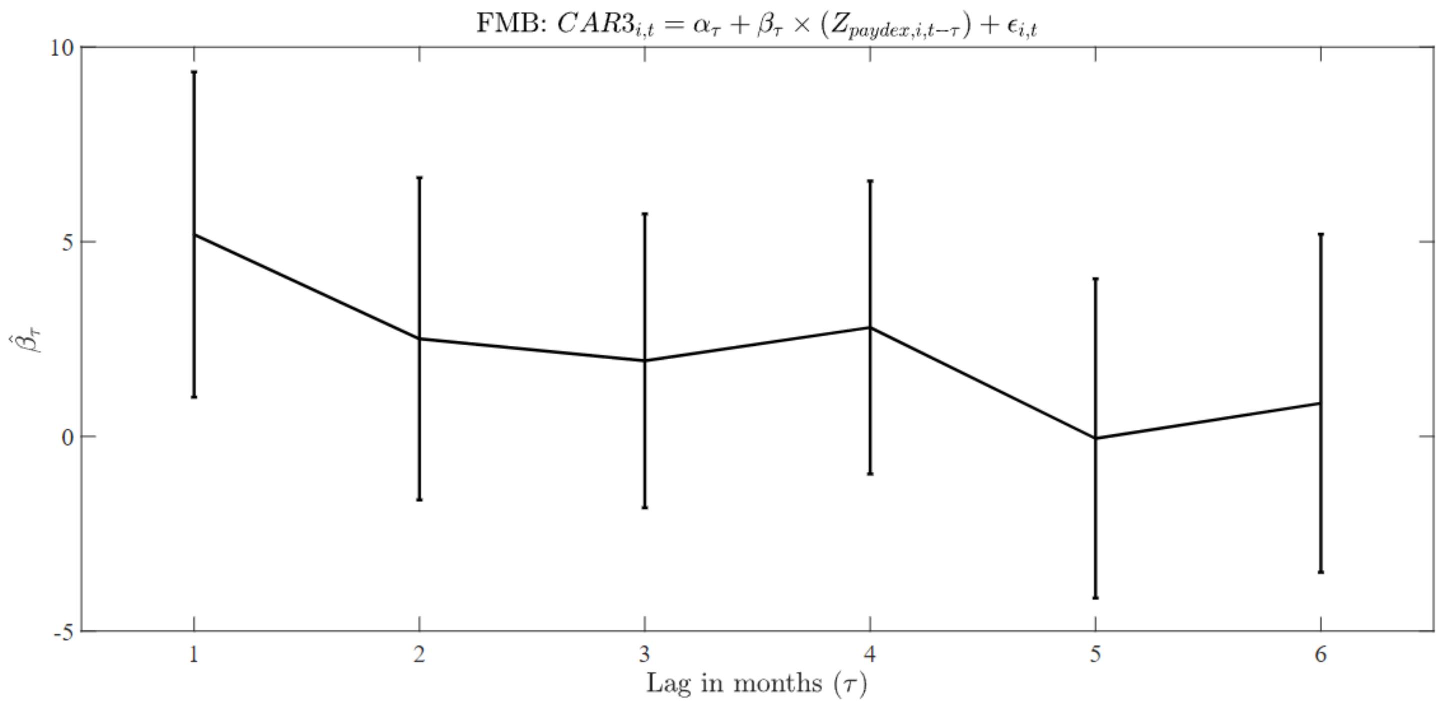
Lieberman et al. (JFE, R&R)

Figure 2: Earnings predictability with Z_{paydex}

The figure plots estimated slope coefficients and 95% confidence intervals from Fama-MacBeth cross-sectional regressions of the form $CAR3_{i,t} = \alpha + \beta \times Z_{paydex,i,t-\tau} + \epsilon_{i,t}$. The dependent variable, $CAR3_{i,t}$, is the three-day cumulative abnormal return for firm i announcing earnings in month t. The independent variable $(Z_{paydex,i,t-\tau})$ is the lagged normalized PAYDEX score, with τ indicating the lag in months. The confidence intervals are calculated using Newey-West standard errors with 24 lags. The sample period used for the estimations of the Fama-MacBeth regressions is 01/2006-12/2019.



Lieberman et al. (JFE, R&R)

Table 7: Z_{paydex} sort performance

This table reports average excess returns, alphas, and loadings on the Fama and French (2018) six-factor model for five portfolios constructed by sorting on Z_{paydex}. At the end of each month, we sort stocks into five portfolios based on Z_{paydex} using NYSE breaks. For each of the five portfolios, and for a portfolio long stocks with high Z_{paydex} and short stocks with low Z_{paydex}, Panel A reports average value-weighted returns in excess of the risk-free rate and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, and the Fama and French (2018) five- and six-factor models. Panel B reports the loadings for the six portfolios on the Fama and French (2018) six-factor model. T-statistics are in brackets. The sample period used is 01/2006-12/2019.

Panel A: Excess returns and alphas on Z_{paydex}-sorted portfolios

	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.57	0.83	0.84	0.71	0.76	0.19
	[1.73]	[2.49]	[2.58]	[2.11]	[2.35]	[1.92]
α^{CAPM}	-0.17	0.08	0.11	-0.05	0.04	0.21
	[-2.68]	[1.11]	[1.63]	[-0.71]	[0.49]	[2.09]
α^{FF3}	-0.15	0.07	0.10	-0.04	0.06	0.22
	[-2.39]	[0.93]	[1.48]	[-0.53]	[0.85]	[2.15]
$\alpha^{\text{FF3+UMD}}$	-0.15	0.07	0.09	-0.04	0.07	0.22
	[-2.37]	[0.96]	[1.44]	[-0.55]	[0.93]	[2.18]
α^{FF5}	-0.16	0.06	0.09	-0.04	0.08	0.24
	[-2.37]	[0.72]	[1.28]	[-0.64]	[1.11]	[2.32]
α^{FF6}	-0.16	0.06	0.08	-0.05	0.09	0.24
	[-2.35]	[0.74]	[1.25]	[-0.65]	[1.16]	[2.34]

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Table 8: Z_{slow} sort performance

This table reports average excess returns, alphas, and loadings on the Fama and French (2018) six-factor model for five portfolios constructed by sorting on Z_{slow}. At the end of each month, we sort stocks into five portfolios based on Z_{slow} using NYSE breaks. For each of the five portfolios, and for a portfolio long stocks with high Z_{slow} and short stocks with low Z_{slow}, Panel A reports average value-weighted returns in excess of the risk-free rate and alphas with respect to the CAPM, Fama and French (1993) three-factor model, Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor, and the Fama and French (2018) five- and six-factor models. Panel B reports the loadings for the six portfolios on the Fama and French (2018) six-factor model. T-statistics are in brackets. The sample period used is 01/2006-12/2019.

Panel A: Excess returns and alphas on Z_{slow}-sorted portfolios

	(L)	(2)	(3)	(4)	(H)	(H-L)
r^e	0.87	0.85	0.81	0.72	0.49	-0.38
	[2.71]	[2.58]	[2.48]	[2.18]	[1.47]	[-3.50]
α^{CAPM}	0.15	0.11	0.08	-0.03	-0.26	-0.41
	[2.12]	[1.70]	[1.03]	[-0.47]	[-3.94]	[-3.81]
α^{FF3}	0.20	0.11	0.07	-0.04	-0.27	-0.47
	[2.93]	[1.73]	[0.86]	[-0.59]	[-4.00]	[-4.40]
$\alpha^{\text{FF3+UMD}}$	0.20	0.11	0.07	-0.04	-0.27	-0.46
	[2.92]	[1.75]	[0.90]	[-0.63]	[-3.97]	[-4.37]
α^{FF5}	0.19	0.09	0.06	-0.04	-0.25	-0.44
	[2.79]	[1.33]	[0.72]	[-0.66]	[-3.56]	[-4.03]
α^{FF6}	0.19	0.09	0.06	-0.04	-0.25	-0.44
	[2.78]	[1.35]	[0.75]	[-0.68]	[-3.54]	[-4.01]

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