Lecture 6

Equity Returns in Cross Section (Part 3)

Other Prominent Predictors of Returns

1. Reversals
2. Liquidity
3. Idiosyncratic volatility
4. Earnings quality
5. Investment/growth

There are hundreds of others, but these are most of the more important ones that are more likely to be true predictors of returns and a reasonable basis for creating a factor

Process for considering these (and other) characteristics/factors as predictors of returns follows the same process as with SMB/HML/MOM

1. Ask: is there a reasonable economic motivation?

2. Examine how correlated is this potential predictor of returns with existing established predictors

3. Univariate sorts, look for a statistically significant relation

4. Bivariate sorts with new predictor and existing predictors, one at a time, look for a statistically significant relation

5. Fama-MacBeth to see if it is really there when you put in the whole set of already existing return predictors

6. Consider constructing a factor portfolio that captures the variation in returns of firms sorted by this characteristic

Reversals

Basic idea: see if positive returns one month are associated with positive or negative returns next month

Data suggests negative relationship (short term reversal)

$$Rev_{i,t} = 100 \times R_{i,t}$$

Correlation	β	*Size*	*BM*	*Mom*
Pearson	−0.02	0.07	0.02	0.02

Reversals (continued)

Will skip the univariate/bivariate sort analysis and go directly to Fama-MacBeth

Fama–MacBeth Regressions Analysis

This table presents the results of Fama and MacBeth (1973) regression analyses of the relation between expected stock returns and reversal. Each column in the table presents results for a different cross-sectional regression specification. The dependent variable in all specifications is the one-month-ahead excess stock return. The independent variables are indicated in the first column. Independent variables are winsorized at the 0.5% level on a monthly basis. The table presents average slope and intercept coefficients along with *t*-statistics (in parentheses), adjusted following Newey and West (1987) using six lags,

	(1)	(2)	(3)	(4)	(5)	(6)
Rev	−0.048	−0.053	−0.051	−0.055	−0.054	−0.063
	(−10.07)	(−10.78)	(−10.65)	(−10.85)	(−11.08)	(−12.54)
β		−0.235				−0.099
		(−1.67)				(−0.61)
Size			−0.106			−0.132
			(−2.13)			(−2.36)
BM				0.415		0.229
				(5.13)		(3.35)
Mom					0.007	0.006
					(2.89)	(3.05)

Liquidity

Basic idea: investors may demand a premium for lack of liquidity

Liquidity can be hard to measure for a large set of stocks. Tradeoff between quality and quantity of data

$$Illiq_i = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{VOLD_{i,d}}$$

$R_{i,d}$ is the return of stock i on day d measured as a decimal (0.01 is a 1% return).

$VOLD_{i,d}$ is the dollar volume of stock i traded on day d, calculated as the closing price of the stock times the number of shares traded on the given date, measured in millions

The value of *Illiq* can be interpreted as the percentage price impact of trading one million dollars where the percentage impact is measured as a decimal (in percent).

Various time windows have been used based on most recent 12/6/3/1 month period

Correlations – consider size carefully

	$Illiq^{12M}$
$Illiq^{1M}$	0.96
$Illiq^{3M}$	0.98
$Illiq^{6M}$	0.99
$Illiq^{12M}$	
ln $Illiq^{1M}$	0.75
ln $Illiq^{3M}$	0.79
ln $Illiq^{6M}$	0.82
ln $Illiq^{12M}$	0.83
β	−0.15
Size	−0.46
BM	0.21
Mom	−0.09
Rev	−0.00

Again, skipping sorts and going to Fama-MacBeth

Panel A: $Illiq^{12M}$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Illiq^{12M}$	0.027	0.022	0.050	0.055	0.037	0.024	0.071
	(1.33)	(1.03)	(2.87)	(2.20)	(1.89)	(1.15)	(3.70)
β		−0.134					−0.151
		(−0.90)					(−0.93)
Size			−0.046				−0.039
			(−0.90)				(−0.74)
BM				0.309			0.192
				(3.63)			(2.54)
Mom					0.010		0.009
					(4.41)		(4.19)
Rev						−0.049	−0.061
						(−9.57)	(−12.18)

Idiosyncratic Volatility

Regress excess returns against a factor model with k factors (k=1 for CAPM, k=4 for FFC-4) and collect the residuals (epsilons)

$$RSE_i = \sqrt{\frac{\sum_{j=1}^{n} \epsilon_{i,j}^2}{n-k}}$$

where n is the number of data points that are used to fit the regression and k is the number of parameters estimated by the regression.

$$IdioVol_i = 100RSE_i \times \sqrt{m}.$$

The term m is for number of periods in a year and the square root of m adjustment effectively annualizes the volatility

Lots of possible choices for *n* and *m* and *k*

Correlations—Idiosyncratic Volatility and Other Variables

	β	*Size*	*BM*	*Mom*	*Rev*	*Illiq*
$IdioVol^{FF,1M}$	0.08	−0.45	0.07	−0.16	0.10	0.48
$IdioVol^{FF,3M}$	0.09	−0.52	0.08	−0.14	0.02	0.49
$IdioVol^{FF,6M}$	0.10	−0.55	0.09	−0.12	0.00	0.50
$IdioVol^{FF,12M}$	0.11	−0.58	0.10	−0.08	−0.01	0.49
$IdioVol^{FF,1Y}$	0.13	−0.42	0.04	0.10	0.04	0.24
$IdioVol^{FF,2Y}$	0.15	−0.48	0.02	0.05	0.01	0.27
$IdioVol^{FF,3Y}$	0.16	−0.50	0.00	0.03	0.00	0.27
$IdioVol^{FF,5Y}$	0.16	−0.51	−0.02	0.01	−0.00	0.28

Fama–MacBeth Regression Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$IdioVol^{FF,1M}$	−0.008	−0.007	−0.014	−0.005	−0.007	−0.006	−0.018	−0.008	−0.008	−0.013
	(−2.52)	(−2.35)	(−5.25)	(−1.44)	(−2.38)	(−1.61)	(−5.39)	(−2.37)	(−2.47)	(−5.85)
β		−0.211								0.004
		(−1.71)								(0.03)
Size			−0.228							−0.179
			(−5.96)							(−4.15)
BM				0.345						0.141
				(4.71)						(1.99)
Mom					0.006					0.007
					(2.94)					(3.85)
Rev						−0.056				−0.059
						(−11.49)				(−11.32)
Illiq							0.096			0.067
							(4.10)			(3.74)

Two final predictors of returns that Fama-French have blessed as factors

Fama and French (2015) → propose a five factor model that adds profitability and investment intensity

$$r_{it} - r_f = \alpha_i + \beta_i(r_{Mt} - r_f) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

where robust minus weak (RMW) is on operating profit and conservative minus aggressive (CMA) is on investments

- High operating profit or low investments tend to imply higher returns

	Low	2	3	4	High
Panel A: Size-B/M portfolios					
Small	0.26	0.81	0.85	1.01	1.15
2	0.48	0.72	0.94	0.94	1.02
3	0.50	0.78	0.79	0.88	1.07
4	0.60	0.57	0.71	0.85	0.86
Big	0.46	0.51	0.48	0.56	0.62
Panel B: Size-OP portfolios					
Small	0.56	0.94	0.90	0.95	0.88
2	0.59	0.78	0.84	0.81	0.98
3	0.53	0.77	0.72	0.78	0.94
4	0.57	0.65	0.63	0.70	0.82
Big	0.39	0.33	0.43	0.47	0.57
Panel C: Size-Inv portfolios					
Small	1.01	0.98	0.99	0.89	0.35
2	0.92	0.91	0.92	0.90	0.48
3	0.90	0.93	0.81	0.82	0.50
4	0.79	0.72	0.71	0.75	0.54
Big	0.71	0.52	0.49	0.48	0.42

- In Fama-French (2015), operating profit, OP, in year t (June) is measured with accounting data for the fiscal year ending in year $t-1$ and is revenue minus cost of goods sold (COGS), minus selling, general, and administrative expenses (SGA), minus interest expense, all divided by book equity.

- Investment, Inv, is the change of total assets from the fiscal year ending in year $t-2$ to the fiscal year ending in $t-1$, divided by $t-2$ total assets.

Does the model "work"?

- FF finds that the five-factor model is formally rejected by the data by jointly testing if the alphas are zero.

  Test assets are (i) 25 size-B/M, 25 size-OP, and 25 size-Inv portfolios and (ii) 32 size-B/M-OP, 32 size-B/M-Inv, and 32 size-OP-Inv portfolios.

  The 25 portfolios are 5×5, and the 32 portfolios are $2 \times 4 \times 4$.

- But the model performs well in terms of R^2 for almost all portfolios.
- The culprit is a particular portfolio.

The discussion of regression details is long, and a summary is helpful. Despite rejection on the *GRS* test, the five-factor model performs well: unexplained average returns for individual portfolios are almost all close to zero. The major exception is a portfolio that shows up in many sorts. The stocks in the offending portfolio are small and have negative exposures to *RMW* and *CMA*; that is, their returns behave like those of firms that invest a lot despite low profitability. In each sort that produces such a portfolio, its five-factor intercept is so negative that, using Bonferroni's inequality, we can easily reject the model for the entire set of 25 or 32 LHS portfolios.

Factor correlations and the redundant HML factor

- In the conventional Fama-French 2×3 sorts (2 portfolios on size, and 3 portfolios on the other dimension), HML is highly correlated with CMA. High B/M firms do little investing.
- FF also do the $2 \times 2 \times 2 \times 2$ sorting, and HML is highly correlated with RMW. High B/M firms tend to have higher profitability, controlling for other factors.
- Formally, FF find that dropping HML doesn't hurt model performance.

Panel C: Correlations between different factors

	2×3 Factors					$2 \times 2 \times 2 \times 2$ Factors				
	$R_M - R_F$	*SMB*	*HML*	*RMW*	*CMA*	$R_M - R_F$	*SMB*	*HML*	*RMW*	*CMA*
$R_M - R_F$	1.00	0.28	−0.30	−0.21	−0.39	1.00	0.25	−0.33	−0.27	−0.42
SMB	0.28	1.00	−0.11	−0.36	−0.11	0.25	1.00	−0.21	−0.33	−0.21
HML	−0.30	−0.11	1.00	0.08	0.70	−0.33	−0.21	1.00	0.63	0.37
RMW	−0.21	−0.36	0.08	1.00	−0.11	−0.27	−0.33	0.63	1.00	0.15
CMA	−0.39	−0.11	0.70	−0.11	1.00	−0.42	−0.21	0.37	0.15	1.00

Source: Fama and French (2015)

Fama and French (2018) reluctantly add momentum to their five-factor model, but with a warning!

We include momentum factors (somewhat reluctantly) now to satisfy insistent popular demand. We worry, however, that opening the game to factors that seem empirically robust but lack theoretical motivation has a destructive downside: the end of discipline that produces parsimonious models and the beginning of a dark age of data dredging that produces a long list of factors with little hope of sifting through them in a statistically reliable way.

Summarizing

1. Covered the portfolio sorting method for discovering excess returns in the cross section of equities and also the Fama-Macbeth regression approach.

2. Discussed the most commonly used factor models

3. Can measure (past) performance of a strategy or fund by examining alpha relative to a factor model

4. Flavor of how quant analysis works. Look for strategies that are not highly correlated with existing predictors of returns and have a believable story behind them.

5. Be a detective in understanding what is driving positive alpha (which subset of securities), realizing that this detective work has a data mining bias associated with it.