Jun Pan
junpan@mit.edu
253-3083
E62-624
MIT Sloan School of Management
15.433-15.4331 Financial Markets, Fall 2016

Classes 6 & 7: Equity in the Cross Section, Part 2

This Version: September 26, 2016

1 The Momentum Profit and the Four-Factor Model

- **Momentum, past and present:** The momentum profit is the strangest thing. You sort stocks by their past returns into past winners and past losers. In the next few months, the winner portfolio keeps "winning" and the loser portfolio keeps "losing." I can imagine the initial reaction received by Prof. Jegadeesh and Titman when they first presented their results: not very warm. If I were there, I would have asked: could there be a coding error?

  Things certainly have changed since 1993, when the momentum paper was first published in the *Journal of Finance*. Now there is momentum everywhere. Since the late 1990s, hedge funds have been doing long/short momentum strategies in equity, international equity, commodity futures, and others. Since the late 2000s, momentum-style equity mutual funds are being offered to "regular" investors; and now you can also buy momentum factor ETFs. Of course, in the world of mutual funds and ETFs, you can only take long positions in the past winners. As a result, the number one risk exposure in these products remains to be the market risk, not momentum.

- **Forming momentum portfolios** The momentum strategy itself is very simple and the exact portfolio formation varies. By now, the strategy adopted by most fund managers is: in month t, sort stocks by their month t-12 to month t-2 cumulative returns. Notice that the returns in month t-1 are intentionally left out. It is well known that, over the one-week up to one-month horizon, stock returns exhibit reversals (the also famous short-term reversal). So including the month t-1 returns would contaminate the momentum signal.

  As usual, let's double sort by size and momentum to get 25 (5x5) portfolios. As shown in Table 1, each portfolio is indexed by size (A to E) and momentum (1 to 5). Our focus is on the momentum dimension, but size is always an important control variable

Table 1: Momentum Portfolios in the CAPM and the Fama-French Three-Factor Model. The 25 portfolios are double sorted by size (from A to E) and past returns (from 1 to 5). All α's are reported in annualized terms (x12). Statistically significant α's are reported in bold. Monthly data from January 1962 to July 2015.

	CAPM				The FF Three Factor Model					
Portfolio	α (%)	t-stat	β	R2 (%)	α (%)	t-stat	β	s	h	R2 (%)
A1	**-8.19**	-3.31	1.37	57.99	**-12.14**	-6.75	1.19	1.24	0.41	78.50
A2	1.68	1.00	1.05	63.57	**-2.46**	-2.66	0.94	0.97	0.52	89.40
A3	**5.01**	3.33	0.99	66.03	1.21	1.56	0.89	0.89	0.48	91.27
A4	**6.57**	4.36	1.00	66.72	**3.39**	4.32	0.88	0.92	0.35	91.26
A5	**8.87**	4.64	1.21	64.28	**6.84**	6.20	0.98	1.14	0.09	88.49
B1	**-7.25**	-3.44	1.45	68.20	**-10.27**	-6.18	1.31	0.95	0.32	80.84
B3	0.95	0.65	1.12	72.39	**-2.38**	-2.47	1.04	0.76	0.42	88.49
B3	**3.47**	2.82	1.03	76.06	0.44	0.60	0.96	0.67	0.39	91.81
B4	**5.69**	4.54	1.05	75.98	**2.92**	4.34	0.95	0.75	0.32	93.31
B5	**6.97**	4.16	1.28	72.38	**5.97**	5.82	1.06	0.95	-0.05	89.99
C1	**-5.54**	-2.78	1.37	68.03	**-7.86**	-4.33	1.29	0.61	0.27	74.17
C2	0.55	0.46	1.10	78.67	**-2.13**	-2.19	1.07	0.46	0.38	86.76
C3	**2.34**	2.18	1.01	80.01	-0.45	-0.59	0.99	0.46	0.40	89.98
C4	**3.19**	3.08	1.01	80.94	0.77	0.97	0.98	0.43	0.34	89.31
C5	**6.87**	4.58	1.21	74.71	**6.51**	5.80	1.04	0.70	-0.11	86.23
D1	**-6.11**	-3.08	1.34	67.05	**-8.24**	-4.24	1.33	0.31	0.31	69.53
D2	-0.05	-0.04	1.11	79.82	**-2.25**	-2.06	1.14	0.17	0.36	83.30
D3	1.83	1.98	1.00	84.15	-0.29	-0.36	1.03	0.16	0.35	88.30
D4	**3.59**	4.26	0.99	86.29	**2.10**	2.69	1.01	0.15	0.23	88.57
D5	**5.49**	4.03	1.15	76.12	**5.52**	4.55	1.03	0.44	-0.12	81.64
E1	**-5.79**	-3.07	1.24	65.92	**-6.68**	-3.54	1.30	-0.13	0.20	66.96
E2	-0.33	-0.28	0.94	73.42	-1.28	-1.12	1.03	-0.20	0.22	76.88
E3	-0.88	-1.08	0.90	84.74	-1.41	-1.90	0.98	-0.20	0.15	87.82
E4	1.20	1.46	0.89	84.10	1.19	1.57	0.95	-0.23	0.06	86.85
E5	**3.30**	2.70	1.02	75.83	**4.47**	3.69	0.99	-0.04	-0.21	76.95

in any trading strategy. Ideally, we would like a strategy to work within each size group, from A to E. And as shown in Table 1, the momentum strategy delivers such a result. It should be noted that I use monthly returns to run the regressions, but report the alpha's in annualized terms for ease of communication (which might be a source of confusion by now). In any case, the reported alpha's in Table 1 are the monthly alpha's multiplied by 12. All other estimates are unaffected.

- **The momentum profit:** By now, I believe that you know how to read and evaluate the numbers in Table 1. So I'll be brief.

  Focusing on one size category, say group A, and varying from A1 to A5, we move from portfolios containing past losers to past winners. You can see the strong magnitudes of these alpha's and their t-stat's: the CAPM alpha is -8.19% per year for A1 and 8.87% for A5. Both estimates are statistically significant with large t-stat's. It is also nice that within each size group, the alpha increases monotonically from group 1 to 5. Moreover, even for stocks in the large cap group, the momentum profit is quite strong and statistically significant: the CAPM alpha is -5.79% for E1 and 3.30% for E5. Recall that for book-to-market, the results are not this strong for group E. Moving to the right side of the Table, we see that the Fama French factors do not help us explain the momentum profit. Not at all.

- **More observations:** By now, some of you might have come to like reading numbers. If so, you could spend even more time on Table 1. Notice how the CAPM beta's for the two extreme portfolios (winner and loser) tend to be larger than the middle three portfolios? This indicates that momentum portfolios tend to be more volatile. Of course, if you are doing the long/short strategy, then the beta exposure decreases to a large extend. Still the momentum strategy tend to be more volatile compared with other strategies (see also page 3 of Prof. Kent Daniel's slides where he reports the standard deviations of the six popular strategies pursued by GSAM.)

  Focusing on the size and value exposures in Table 1, you might also notice that the winner portfolios tend to have negative exposures to HML while the loser portfolios tend to have large and positive exposures to HML. This tells you that there is an interaction between these two signals: growth stocks tend to be past winners or past winners tend to be growth stocks. So to sharpen your momentum signal, you might want to take advantage of this interaction term: hold past winners with high book-to-market ratio and sell past lowers with low book-to-market ratio.

- **Paper alpha vs. real alpha:** While the momentum profit looks impressive on paper, the real alpha of the trading strategy might not be as impressive because of the execution costs involved with high portfolio turnovers. For example, the annual turnover of a small-cap momentum mutual fund is close to 200%. So the real alpha of the strategy will be cut by transaction costs. One of the main sources of transaction costs is price impact, especially for a large fund pursuing momentum strategy in small-cap stocks, where liquidity is known to be poor.

In general, keeping the execution costs low should be as important as generating alpha. Low execution costs contribute directly to portfolio performance. In today's trading environment, knowing how to trade large institutional-size portfolios to minimize transaction costs separates a good asset manager from a mediocre one.

- **Momentum in mutual funds and ETFs:** For long-only equity mutual funds or ETF pursuing momentum strategies, the typical momentum portfolio contains stocks that are ranked by past performance among the top 1/3. For example, if we focus on large-cap stocks in groups E, then the momentum portfolio is a value-weighted portfolio of all the stocks in our E5 plus the top half of E4. For small-cap momentum funds, it is a value-weighted portfolios of all the stocks in our A5 and the top half of A4. As you can see in Table 1, such portfolios do have positive alphas. At the same time, however, they also have a pretty large exposure to the market risk. In other words, by holding a momentum portfolio, an investor's number one risk exposure is not really momentum. By pushing quant investing into the long-only space, the razor-sharp focus on the targeted risk is lost because of the inability to do long/short.

- **The four-factor model:** Because the momentum profit cannot be explained by the Fama-French factors, we add the momentum factor to the FF three-factor model to form a four-factor model:

$$E(R_t^i) - r_f = \beta_i \left(E\left(R_t^M\right) - r_f\right) + s_i\, E\left(R_t^{\text{SMB}}\right) + h_i\, E\left(R_t^{\text{HML}}\right) + w_i\, E\left(R_t^{\text{MOM}}\right) \,,$$

where the new MOM factor is constructed in a way similar to the HML factor. Along the size dimension, stocks are sort into two groups: small or big. Along the momentum dimension, stocks are sort into three groups with 30% in high past returns, 40% in neutral, and 30% in low past returns. Again, because these portfolios are to be used to construct factors, one would like to have them as diversified as possible. Hence the coarser sort. Using these portfolios, the momentum factor is constructed as,

$$R^{\text{MOM}} = R^{\text{winner}} - R^{\text{loser}} \,,$$

where R^{winner}=1/2 (small high + big high) and R^{loser}=1/2 (small low + big low). Finally, the factor exposures (β, s, h, w), can be estimated using the four-factor regression:

$$R_t^i - r_f = \alpha_i + \beta_i \left(R_t^M - r_f\right) + s_i \, R_t^{\text{SMB}} + h_i \, R^{\text{HML}} + w_i \, R^{\text{MOM}} + \epsilon_t^i \, .$$

This four-factor model is also call the Carhart model, because it was first proposed in a 1997 Journal of Finance paper written by Mark Carhart to examine the performance of equity mutual funds. Carhart was a PhD student of Prof. Fama and helped run the Global Alpha fund, founded by Cliff Asness in the late 1990s, at GSAM. At its peak, the team managed over $185 billion in assets. In 2011, the fund was closed by Goldman. It marked the end of an era.

- **Using the four-factor model:** The four-factor model can be used as a benchmark model to evaluate the performance of fund managers. A fund manager following momentum strategy might have a pretty nice looking FF3 alpha, but when evaluate his performance against the four factor model, his four-factor alpha might be insignificant. This implies that most of his FF3 alpha comes from exposures to the momentum factor. Again, "beta in disguise."

2 Quant Investing: crowded trades, over-used signals

- **Popular quant signals:** By now, there is a set of well established quant signals, with size, value, and momentum being the most basic collection. For example, in Prof Kent Daniel's slides, he mentioned six quant-style portfolios held by GSAM's Global Equity Opportunities funds around 2007.

  Value and momentum are two of the six quant signals. In addition, profitability, measured as the earnings-to-sales ratio, is also a useful quant signal. Recently, Fama and French propose a profitability signal that uses the operating profit (=revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense) divided by book value of equity. They find that stocks with robust profitability overperforms stocks with weak profitability and create a factor called RMW (robust minus weak).

  By now, you might notice that accounting data plays a pretty important role in signal creation. This indeed is true. Many of the quant signals were first reported by accounting professors. The quant signals relating to earnings quality is one such example. In a 1996 paper published in the *Accounting Review*, Prof Sloan shows stock prices do not fully reflect the information in the quality of earnings. Stocks with low earnings quality (high accrual) underperform stocks with high earnings quality.

The quant signal using analysts forecast revision also comes from the accounting literature. In a 1991 paper, also published in the *Accounting Review*, Prof Stickel finds that analysts revision affect prices, but prices do not immediately assimilate the information. In fact, prices continue to drift in the direction of the revision for about six months after the revision. Another important pattern related to earnings news is reported by Bernard and Thomas (1989). This is the famous post earnings announcement drift: stocks with positive earnings surprises on their announcement day keep drift upward in their stock prices a few weeks (up to 60 days) after the announcement while stocks with negative earnings surprises keep drifting downward.

Finally, the sixth signal reported in Prof Kent Daniel's slides is management impact. This signal builds on two observations. Loughran and Ritter (1994) reports long-term underperformance after IPO or SEO (seasoned equity offering), and Ikenberry, Lakonishok, and Vermaelan (1995) reports long-term overperformance after announcements of share repurchases. In their recent paper, Fama and French introduces a signal that is similar in spirit. They use the firm's asset growth as a signal for firm investment. They find that stocks with low investment (low asset growth) outperform stocks with high investment. Calling firms with low investment conservative, and high investment aggressive, Fama and French introduce a new factor called CMA (conservative minus aggressive). Together with the market portfolio, SMB, HML, RMW (just mentioned), Fama and French build a new five-factor model.

- **Crowded trades and over-used signals:** By now, popular quant signals are a common knowledge. This is an over-crowded space with over-used signals. Moreover, the transparency of these trading strategies also makes the funds easy to predict, inviting front runners.

  The 2007 quant meltdown is clearly a result of over-crowding. This example itself is interesting, but the lesson to be learned is not confined just to this one space. To a large extent, the 1998 LTCM crisis was a parallel example in the fixed income arbitrage space. Since the mid-1980s, the fixed-income market has enjoyed a great bull run with an overall trend of decreasing interest rates (from double digits). By the early 1990s, many fixed income arbitrage funds are having a lot of success. Success breeds imitation.

As a result, the market became over-crowded with many hedge funds in the space of fixed-income arbitrage, doing similar yield curve trading. Sounds familiar?

In the case of LTCM, the actual trigger was Russia's default on its local currency debt, which LTCM did not have a lot of exposure to. Similarly, the initial trigger for the 2007 quant meltdown was disruptions in the sub-prime mortgage market, which most of the quant funds did not have any direct holdings. The sub-prime disruption later spilled over to the credit market, and to currency carry trades. At the time, what many quant investors didn't realize was that the success in their space attracted participation from investors outside of the quant space: statistical arbitrage and other multi-strategy hedge funds.

As the multi-strategy hedge funds experienced the disruptions in the other markets, they sought to liquidate assets to raise more cash. The least costly and the quickest approach is to liquidate the most liquid holdings, which are the stocks in their quant strategies. Hence the typical contagion story. The quant stocks started to spiral down together not because they shared some negative fundamentals. Instead, the co-movement was caused by the commonality in who were holding these stocks: quant funds. For the 2007 quant meltdown, you need a special pair of quant goggles to see it. Otherwise, the market looked quite normal during the first two weeks of August 2007. But in the quant world, the portfolios were moving down by as much as 20 sigmas. The draw-down affected all quant strategies in all geographical regions.

Similarly, back in 1998, the wall street firms had all the incentive to save LTCM because they were holding similar assets and pursue the same trading strategies as LTCM. If LTCM liquidated their portfolios to the market, the liquidity crisis will bring down many of the investment banks. You might wonder: a liquidity crisis is only temporary, why worry? Everything will bounce back, right? For example, in the second half of August 2007, the quant funds rebounded and things were back to normal. Well, if you are holding a leveraged position, then this is a totally different story: you might not be able to survive the temporary liquidity crisis. Being levered during a liquidity crisis brings into my mind the picture painted by one of Warren Buffett's famous quotes: Only when the tide goes out do you discover who's been swimming naked.

In the case of LTCM, the leverage of of the fund has been widely documented and the often quoted number is 30 to 1. (See, for example, the book by Roger Lowenstein). In the case of the quant meltdown, Bob Litterman gave this description of GSAM's Global Equity Opportunities fund. There were +1000 positions on individual stocks, with an average holding period in months. The portfolio is market neutral and industry neutral, with a volatility of about 10% per year and 1.4% per week. Up to 2007, the average return was about 15% per year. In July 2007, however, it was down 15%. The overall size of the fund was about \$6 billions, with \$24 billion long/short positions. So effectively, with \$6 billion equity, the firm's assets were at around \$48: 8 to 1. From August 1 to 10, the fund was down 30%, an over 20 sigma drawdown.

- **What next?** The lessons learned from the quant meltdown:
  - cannot be too big: whale.
  - cannot be too crowded: run for the exit.
  - cannot be too transparent: front running.

  Clearly, it is important to have your unique trading strategies. As such, the search for new quant signals is still on. Given the massive amount of "data mining" in the past ten to twenty years, the amount of interesting signals left for us to discover might be limited. Overall, this area is just not as exciting and creative as it was ten or twenty years ago.

  An alpha that looks good on paper does not necessarily translate to real alpha. Transaction costs such as price impact or short-sale constraint cut into the real alpha. This is especially true for smaller and less liquid stocks. Unfortunately, most of the quant signals work better in small to medium stocks. Another problem is that some quant signals that used to work in the past ceased to work after the publication of the signal.

  One push is to other asset classes, such as fixed income. But the fixed-income world is probably smarter and faster than the equity world in the sense that most of the fixed income arbitrage trades are indeed designed to exploit cross-sectional pricing differences. For the corporate bond market, the lack of liquidity in that market does not make it a suitable place for the traditional quant investing.

  Another recent push is to mutual funds and ETFs. As we discussed earlier, for long-only space, a large portfolio of the risk exposure comes not from the quant signal, but from the market risk. This probably is the most limiting aspect of quant investing in this space. Nevertheless, the push in that direction seems to be a recent trend. In yesterday's *Financial Times*, it was reported that Goldman has also joined the "smart beta" ETF rush.

3 Currency Carry Trade

- **The FX market:** In terms of trading, the foreign exchange market is the largest and the most liquid market in the world. According to a BIS survey in 2013, the daily trading volume of the currency market was $5.34 trillion, among which the dollar trading volume in the spot market was around $2 trillion. By comparison, the average daily dollar trading volume of NYSE group is $41 billion in 2015. The US Treasury market, important and highly liquid, has a daily dollar trading volume around $500 billion. There are mixed trading motives behind the trillion dollar daily trading volume: hedging currency exposure could be an important component, but currency speculation accounts for a sizable percentage of the trading volume.

- **Currency carry trade:** Currency carry trade is one of the well known trading strategies pursued by macro hedge funds. In a way, it is like quant investing, except that the history of this trading strategy is probably longer than quant investing in the equity space. Fama (1984) was one of the earlier papers documenting this pattern, which is called forward premium puzzle in academic.

  The strategy is simple and intuitive. Currencies with high interest rates (e.g., New Zealand dollar or Australia dollars) are used as asset or target currencies and currencies with low interest rates (Japanese Yen) are used as funding currencies. The strategy is to buy the "target" currencies and borrow from the "funding" currency, carry this position with a positive carry, and unwind it later in the spot market: sell the target currency and buy back the funding currency. As a result, there are two drivers for the portfolio returns: the interest rate differential, and the gain or loss in the spot market when unwinding the trade. It is very similar to the two components in stock returns: dividend yield and capital gains.

  On average, this is a profitable trading strategy, but it is sensitive to the liquidity condition of the global markets. Large losses in currency carry often incurs when there is a global sell-off of risky assets. In a flight to quality, investors typically abandon the risky assets and move to the safer securities such as US treasury or the perceived safe haven currencies (e.g., the Swiss Franc, the Japanese Yen, and the US dollars). Accompanied with the large losses in currency carry is the sudden strengthening of the funding currency and weakening of the target currency. As carry traders rush to the market to unwind their carry trades, the situation is further exacerbated.

- **Currency Carry Profit:** Let's apply the portfolio approach we've learned from the quant investing to currency carry. Let's use the US dollar as an anchor and calculate portfolio returns from the perspective of a US investor. In month t, he borrows in US dollar and buys one specific foreign currency. In month t+1, he unwinds the trade and calculates the realized return.

In forming the portfolios, we use the interest rate differential between the foreign and US one-month risk-free rates, $i^* - i$ as the quant signal. We sort foreign currencies into six groups. Group 1 contains currencies with the highest interest rates: the target currencies. Group 6 contains currencies with the lowest interest rates: the funding currencies. For each portfolio, we calculate the holding period returns from each currency and equal weight the returns across the currencies in the portfolio.

Table 2: Currency Portfolios Sorted by Interest Rates

		CAPM	
Rank	exret (%)	beta	alpha (%)
1	0.79	0.19	0.69
	[4.56]	[3.08]	[3.22]
2	0.35	0.17	0.26
	[2.39]	[3.64]	[1.55]
3	0.28	0.12	0.22
	[2.14]	[2.36]	[1.39]
4	0.15	0.08	0.11
	[1.21]	[1.91]	[0.77]
5	-0.05	0.07	-0.08
	[-0.38]	[1.53]	[-0.58]
6	-0.18	0.01	-0.18
	[-1.37]	[0.24]	[-1.30]

Table 2 uses monthly data from January 1987 through December 2011. The number of available currencies varies over time. For the period from 1987 through 2011, the sample starts with 17 currencies and reaches a maximum of 34 currencies. Since the launch of Euro in January 1999, the sample covers 24 currencies.

The average excess return for portfolio 1 is 0.79% per month and is statistically significant. By comparison, the average excess return for portfolio 6 is slightly negative and is insignificant. A typical currency carry trade would long portfolio 1 and short portfolio 6. The difference between these two portfolio returns constitutes the typical currency carry profit: around 0.97% per month (roughly 11% per year). Using the US stock market portfolio as a benchmark, we find that the portfolio of target currencies has a beta of 0.19, which is interesting given that the portfolio involves positions on currencies with no direct exposure to the stock market. By contrast, the portfolio of funding currency has very little exposure to the US stock market. Overall, the CAPM alpha of the currency carry trade remains large and significant.