OVER THE Top

Investor overconfidence meets momentum, reversal and market state.

BY RICHARD DEAVES AND PETER MIU

To researchers, momentum is a well-documented anomaly. To practitioners it is a robust strategy. Jegadeesh and Titman (1993), using U.S. data, were the first ones to carefully document the efficacy of using momentum as a screen in portfolio formation. They found, for example, that a long-short, zero-cost portfolio formed on the basis of returns over the previous six months earns an average excess return of 0.95% per month over the next six months. To researchers this finding is anomalous because, up until now, theoretical asset-pricing models have been unable to convincingly explain it. Today the three-factor model of Fama and French (1993) has become a conventional (if not unanimously accepted) way to risk-adjust.[1] Problematically, this model, which incorporates market, size and value as risk controls, is unable to explain momentum (Fama and French (1996)). Nor is the momentum phenomenon confined to the U.S., with both Rouwenhorst (1998) and Griffin, Ji and Martin (2003) providing international corroboration.[2] In previous work concentrating on Canadian markets, Cleary and Inglis (1998) and Deaves and Miu (2007) also document reliable momentum.[3] The former researchers, for example, using data from 1979 to 1990, find excess momentum returns of 4.10% per quarter.[4]

Deaves and Miu (2007) also show that the momentum phenomenon in Canada may have started to dissipate. While this dovetails well with a flexible market-efficiency view of the world where anomalies, once uncovered, are eventually arbitraged away, it is also consistent with the adaptive markets hypothesis of Lo (2004), who has recently suggested that cyclicality in strategy profitability is to be expected in a world where markets are subject to evolutionary forces. Opportunities that exist because of faulty heuristics and limits to arbitrage may evaporate since "given enough time and competitive forces, any counterproductive heuristic will be reshaped to fit the current environment." On the other hand, if some of those exploiting particular opportunities leave the market, profitability may be rekindled.

Whatever the reasons may be for this dissipation, a judicious implementation of momentum will be predicated on when it is likely to work and when it is likely to fail. Along these lines, Grinblatt and Moskowitz (2004) condition on the term structure of prior returns. Consistent with the reversal effect first documented by De Bondt and Thaler (1985), they find that while intermediate-term returns (3-12 months) are positively correlated, longer-term returns are negatively correlated. This suggests that a superior term structure filter would be

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to look for positive recent returns (say the last six months) and negative longer-term returns (say the previous two-three years). Indeed, Deaves and Miu (2007) show that paying attention to both momentum and reversal enhances profitability in the Canadian environment.

Other research has explored the relationship between momentum and the state of the economy or the market. Chordia and Shivakumar (2002) argue that macroeconomic variables account for a large portion of momentum profits, and, since these are likely risk factors, much momentum profitability is illusory. Other researchers have questioned these findings on methodological and empirical grounds (Cooper, Gutierrez and Hameed (2004) and Griffin, Ji and Martin (2003)). As for the state of the market, Cooper, Gutierrez and Hameed show that momentum profitability in the U.S. exists exclusively after up-market states. They argue that there is a compelling behavioural explanation for this finding. This explanation also embeds an explanation of unconditional momentum and reversal.

To elaborate, there is abundant evidence that most of us most of the time are overconfident, which means we overestimate the precision of our knowledge (see Deaves, Lüders and Luo (2006) for numerous citations). Daniel, Hirshleifer and Subrahmanyam (1998) show that overconfidence leads to overreaction in markets. When a group of investors receives a common private signal (for concreteness, imagine that they have revised upwards the earnings growth rate in response to shared perception of enhanced future sales opportunities), their trading activity will push prices in the correct direction, but there will be a tendency for overreaction. This is because they will take this private signal (which is after all a noisy one) too much at face value and will ignore other fundamental factors. Prices that are pushed too high/low will eventually fall back/rise up as the true nature of the information is digested by the market. The result of this is excess volatility and long-run reversal.

To generate momentum along with reversal, we need not just overconfidence but also self-attribution bias. Self-attribution bias is the tendency for us to vividly recall our successes while being somewhat hazy about our failures (e.g., Langer and Roth (1975)). Problematically, this makes it more difficult for us to obtain an accurate sense of our knowledge. Everybody has talked to cocktail-party pundits who regale us with their greatest stock pick, while neglecting to tell us about their 10 worst dogs. So triumphs lead to increases in overconfidence, with defeats having less impact in the opposite direction. Return to the group of investors who received a private signal and whose buying activity pushed prices up. This confirming news (prices have risen, so apparently they were right) causes an increase in their overconfidence, a belief in even greater knowledge precision and concomitant further buying activity from this group (leading to continued upward price pressure). The result: momentum and (once again) eventual reversal.

It has been argued that if the overall market is on the rise, many people will become overconfident at the same time (Cooper, Gutierrez and Hameed (2004)). That is to say, aggregate overconfidence increases on market upswings. Theoretical models indicate (see Odean (1998) for example) that higher levels of overconfidence are associated with higher levels of trading activity. Statman, Thorley and Vorkink (2006) provide indirect corroborating evidence at the level of the market, documenting that when the market rises, total trading activity also rises—a finding that is perfectly consistent with an increase in aggregate overconfidence. Deaves, Lüders and Schröder (2006) also provide confirming evidence. In a survey of German stock market forecasters, participants are asked for estimates of the future level of the DAX and a 90% confidence interval bracketing their estimate. When the German market rises, these intervals tend to narrow, once again reflecting a positive correlation between overconfidence and market returns. Because overconfidence is behind momentum, the enhanced overconfidence in up markets leads to greater momentum in up markets.[5]

To our knowledge, no one has yet explored whether reversal is conditional on market state. We conjecture that it is, and, once again, there is a behavioural explanation. Specifically, we argue that reversal should be stronger in down markets. Reversal is all about the market realizing that it has overreacted, leading to prices moving to more sustainable levels. In other words, it is tantamount to a market dominated more by rationality than by psychology. This makes perfect sense in the context of the previous discussion. In down markets, overconfidence declines, and valuations are more likely to be driven by realistic appraisals. Down markets therefore promote the speedy corrections of any previous overreactions in stock prices. It becomes more likely to result in a downward (upward) correction of price of previous winner (loser). This seems to be an environment that is ideal for a strengthened reversal effect, thus leading to higher profits from a reversal strategy. The purpose of this paper is to explore in the Canadian environment momentum and reversal conditional on market state. We believe that this exercise is valuable to practitioners in its potential ability to refine the momentum and reversal screens.

RETURN PREDICTABILITY

To investigate whether Canadian returns have historically been predictable from prior returns, we use monthly returns on the common equity of a total of 974 firms, obtained from the intersection of the Toronto Stock Exchange (TSX)—Canadian Financial Markets Research Centre (TSX-CFMRC) and COMPUSTAT databases over the period June 1985-May 2004.[6] Return predictability in the same direction as prior intermediate-term returns, which is commonly known as momentum, is next documented using the procedure of Jegadeesh and Titman (1993).[7]

TABLE 1

MEAN EFFECTIVE MONTHLY RETURN (%) OF MOMENTUM STRATEGY FROM JUNE 1985 TO MAY 2004

	P1	P2	P3	P4	P5	P5-P1
Panel A: Average Compounded Return						
N	222	222	222	222	222	222
Raw return	0.50	0.48	0.88	1.33	2.01	1.08
(*t*-statistic)	(0.89)	(1.40)	(3.03)	(4.41)	(4.67)	(2.67)
CAPM-adjusted	-0.30	-0.28	0.14	0.59	1.23	1.10
(*t*-statistic)	(-0.75)	(-1.35)	(0.87)	(3.11)	(4.45)	(2.73)
Fama-French-adj.	-0.55	-0.51	-0.07	0.38	1.07	1.22
(*t*-statistic)	(-1.88)	(-3.79)	(-0.67)	(2.81)	(5.02)	(3.17)
Panel B: Average Compounded Return Following 12-month UP Markets						
N	155	155	155	155	155	155
Raw return	0.16	0.32	0.77	1.21	1.87	1.45
(*t*-statistic)	(0.25)	(0.82)	(2.20)	(3.31)	(3.74)	(3.31)
CAPM-adjusted	-0.70	-0.45	0.01	0.46	1.08	1.46
(*t*-statistic)	(-1.54)	(-1.90)	(0.07)	(2.31)	(3.77)	(3.36)
Fama-French-adj.	-0.84	-0.63	-0.16	0.29	0.99	1.54
(*t*-statistic)	(-2.79)	(-4.08)	(-1.33)	(1.97)	(4.31)	(3.75)
Panel C: Average Compounded Return Following 12-month DOWN Markets						
N	67	67	67	67	67	67
Raw return	1.31	0.83	1.15	1.61	2.36	0.24
(*t*-statistic)	(1.33)	(1.56)	(2.76)	(4.22)	(3.88)	(0.31)
CAPM-adjusted	0.61	0.13	0.45	0.88	1.58	0.26
(*t*-statistic)	(0.91)	(0.45)	(1.74)	(3.06)	(3.65)	(0.34)
Fama-French-adj.	0.13	-0.23	0.13	0.58	1.26	0.48
(*t*-statistic)	(0.23)	(-1.13)	(0.73)	(3.04)	(3.95)	(0.64)
Panel D: Test for Equality (UP – DOWN = 0)						
Raw return	-1.05	-0.82	-0.76	-0.85	-0.72	1.40
CAPM-adjusted	-1.69	-1.71	-1.54	-1.45	-1.17	1.40
Fama-French-adj.	-1.50	-1.68	-1.48	-1.48	-0.83	1.26

Securities are ranked by prior intermediate-term returns, and then formed into five quintiles.[8] The top 20% of stocks by past return are put into quintile 5 (P5), the next highest group are put into quintile 4 (P4), and so on, down to quintile 1 (P1), which has the 20% of stocks with the lowest returns. While prior intermediate-term returns are typically measured over 3-12 month intervals, and future returns are measured over comparable intervals, here, for brevity, we focus on six months (both looking back and forward).[9] Since we expect the P5/P1 portfolio to perform best/worst, most mileage is achieved by going long P5 and short P1 in order to create the zero-cost portfolio referred to as P5-P1.

In Panel A of Table 1, we report the mean compounded return (expressed on an effective monthly return basis), along with corresponding *t*-statistics, for portfolios P1 through P5, as well as for P5-P1. In addition to working with raw returns, we also present risk-adjusted returns (alphas) using two conventional risk-adjustment approaches, CAPM and the Fama-French three-factor model.[10] Since the time-series of compounded raw returns (and alphas) are overlapping, we compute the *t*-statistic using the autocorrelation-consistent covariance estimator of Newey and West (1987), setting the number of lags equal to the number of overlapping months (i.e., a lag of five for a six-month holding period).

Notice that raw returns and alphas are higher the higher were past intermediate-term returns. The raw return of P5, for example, is 2.01%/month, vs. 0.50%/month for P1. And, using the Fama-French three-factor model, the zero-cost P5-P1 portfolio earned an average of 1.22%/month, a result that is strongly statistically significant.

We next investigate whether the state of the market has any role to play in explaining the profits from momentum strategies. Recall that Cooper, Gutierrez and Hameed (2004) show that in the U.S. momentum is entirely an up-market phenomenon. At each month-end, we define the state of the market as either up or down by observing the return on the CFMRC value-weighted index over the 12 months prior to each holding period.[11] It is defined as an up (down) market if the 12-month return is non-negative (negative). In Panels B and C of Table 1, we report the mean returns of the six-month momentum strategy following up and down markets, as estimated by regressing the time-series of compounded raw returns or alphas against an up dummy variable and a down dummy variable. We again adjust the standard errors for autocorrelation according to Newey and West (1987). We also conduct a hypothesis test on whether the mean returns are identical following up and down markets by regressing the compounded returns

against an intercept and an up dummy variable, with the relevant *t*-statistics being reported in Panel D of Table 1.

Somewhat different from Cooper, Gutierrez and Hameed (2004), we find that in Canada the average returns of the momentum strategy are positive in both up and down markets. For example, using Fama-French risk-adjustment, the P5 portfolio in up/down markets earned 0.99%/1.26%, vs. the P1 portfolio which earned -0.84%/0.13%. Importantly though, similar to Cooper, Gutierrez and Hameed, momentum can generate raw returns and alphas that are strongly statistically significant only in up markets. Returns on a momentum strategy in down markets, however, are not statistically significant. The lacklustre profitability stems from the much better performance of the previously poorly performing stocks (i.e., quintile P1) in down markets. The monotonic (positive) relationship between prior intermediate-term returns and future six-month returns does not hold anymore in down markets. Nevertheless, one should note that the difference in profitability between up and down markets falls short of conventional statistical significance levels.

REVERSAL AND MARKET STATE

We next investigate reversal profitability, first unconditional on market state, and second conditional on market state. Here, rather than ranking securities according to their prior intermediate-term (six-month) returns, we now sort stocks based on prior long-term returns. Specifically, we look at returns from 2.5 years back to six months back.[12] The top 20% of stocks by past return over this time period are put into quintile 5 (Q5), the next highest group are put into quintile 4 (Q4), and so on, down to quintile 1 (Q1), which has the 20% of stocks with the lowest returns. Future performance of these five quintiles is, once again, measured over the following six months.

Table 2 is exactly analogous to Table 1, except that portfolios are conditioned on prior long-term returns rather than on prior intermediate-term returns. In Panel A, we observe that reversal is also an effective strategy in the Canadian market. In general, raw returns and alphas are higher the lower were past long-term returns. For example, Q1's mean raw return is 1.84% while Q5's is 0.41%. In Panels B and C, we see that, unlike in the case of momentum, reversal works better in down markets, generating raw returns and alphas that are strongly statistically significant. A zero-cost portfolio of taking a long position in Q1 while shorting Q5 in down markets yields a Fama-French alpha of 3.19%/month. The profitability in up markets is, however, much lower and of weaker statistical significance. Moreover, the difference in profitability between up and down markets is now statistically significant at 10% or better, whether we use raw returns, CAPM-alphas or Fama-French alphas.

MIXED MOMENTUM/REVERSAL STRATEGY

We next probe the economic significance of these findings by simulating the benefit of employing a mixed momentum/reversal strategy contingent on market state in enhancing an index portfolio over our sample period. Starting from the beginning of July 1985, we invest $(1/6) in a portfolio that is made up of three components (i.e.,

TABLE 2

MEAN EFFECTIVE MONTHLY RETURN (%) OF REVERSAL STRATEGY FROM JUNE 1985 TO MAY 2004.

	Q1	Q2	Q3	Q4	Q5	Q1-Q5
Panel A: Average Return						
N	222	222	222	222	222	222
Raw return	1.84	1.21	0.72	0.79	0.41	2.26
(*t*-statistic)	(3.29)	(3.15)	(2.83)	(3.23)	(1.09)	(3.60)
CAPM-adjusted	1.03	0.44	-0.01	0.06	-0.36	2.19
(*t*-statistic)	(2.40)	(1.64)	(-0.05)	(0.39)	(-1.62)	(3.56)
Fama-French-adj.	0.58	0.07	-0.24	-0.10	-0.44	1.59
(*t*-statistic)	(1.63)	(0.44)	(-2.11)	(-0.84)	(-2.37)	(3.04)
Panel B: Average Return Following 12-month UP Markets						
N	155	155	155	155	155	155
Raw return	1.29	0.91	0.59	0.77	0.32	1.37
(*t*-statistic)	(2.04)	(2.08)	(2.01)	(2.60)	(0.71)	(2.58)
CAPM-adjusted	0.45	0.13	-0.16	0.03	-0.47	1.31
(*t*-statistic)	(0.98)	(0.46)	(-0.94)	(0.17)	(-1.94)	(2.54)
Fama-French-adj.	0.13	-0.17	-0.35	-0.11	-0.53	0.90
(*t*-statistic)	(0.36)	(-0.95)	(-3.29)	(-0.76)	(-2.48)	(1.91)
Panel C: Average Return Following 12-month DOWN Markets						
N	67	67	67	67	67	67
Raw return	3.12	1.90	1.03	0.84	0.64	4.32
(*t*-statistic)	(3.53)	(3.70)	(2.55)	(2.38)	(1.12)	(2.99)
CAPM-adjusted	2.37	1.18	0.34	0.13	-0.09	4.23
(*t*-statistic)	(3.48)	(3.12)	(1.35)	(0.60)	(-0.25)	(2.98)
Fama-French-adj.	1.62	0.63	0.03	-0.09	-0.25	3.19
(*t*-statistic)	(2.51)	(2.80)	(0.16)	(-0.53)	(-0.89)	(2.77)
Panel D: Test for Equality (UP – DOWN = 0)						
Raw return	-1.80	-1.70	-0.97	-0.15	-0.49	-1.93
CAPM-adjusted	-2.50	-2.70	-1.86	-0.41	-1.02	-1.95
Fama-French-adj.	-2.15	-3.19	-1.88	-0.09	-0.90	-1.88

indexed, long and short): (1) a $(1/6) long position in the CFMRC value-weighted index; (2) a $(1/6) long position in P5 (Q1), if it was an up (down) market during the previous 12 months; and (3) a $(1/6) short position in P1 (Q5), if it was an up (down) market. Such a dynamic strategy allows us to capitalize on the above findings of higher return on the momentum (reversal) strategy subsequent to an up (down) market. This first portfolio is held over a six-month period (i.e., until end of December 1985), at the end of which the gross return is realized and reinvested in a new portfolio formulated in the same fashion. We track six-month rollover gross returns generated up to the end of our sample period. We initiate the same investment strategy at the beginning of each month from August 1985 to December 1985 by always investing $(1/6) as described above. We therefore invest a total of $1 during the second half of 1985, and continue rolling over the six mini-portfolios until the end of our sample period in 2004.

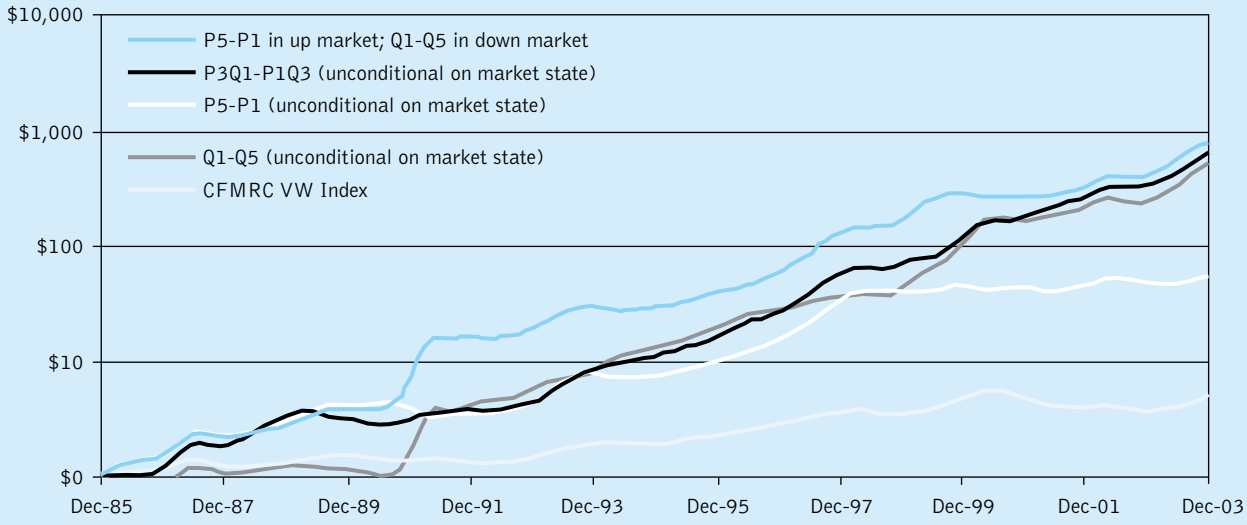
We compare the cumulative return on this market state-conditioned mixed momentum/reversal strategy with several benchmarks that are unconditional on market state.[13] The first benchmark is simply investing in the CFMRC value-weighted index.The second benchmark is an enhanced indexation strategy, based on trading on momentum without conditioning on the state of market. That is, we always take a long (short) position in P5 (P1) whether it is an up market or not. Similarly, the third benchmark is an enhanced indexation strategy, based on trading on reversal without conditioning on the state of market. That is, we always take a long (short) position in Q1 (Q5) whether it is an up market or not. A fourth benchmark follows Deaves and Miu (2007), where a two-way sort over both intermediate-term and long-term returns is conducted. We begin with momentum terciles, and within terciles go on to form reversal terciles. The end result then is the formation of nine portfolios: P1Q1, P1Q2, P1Q3, P2Q1, P2Q2, P2Q3, P3Q1, P3Q2, and P3Q3.[14] For example, P1Q1 denotes the portfolio formed by selecting the bottom 1/3 of stocks in terms of past returns over the last six months, followed by selecting the 1/3 of stocks within this group which are in the bottom 1/3 in terms of past returns from 30 to six months back. Deaves and Miu (2007) show that a zero-cost portfolio of taking a long position in P3Q1 while shorting P1Q3 allows one to benefit from both momentum and reversal strategies simultaneously. Thus, enhancing an indexed portfolio by going long P3Q1 and short P1Q3, unconditional on the state of the market, serves as our fourth benchmark. The cumulative gross returns on these strategies are plotted in Figure 1.

It is apparent that conditioning on either intermediate-term returns (i.e., playing momentum); on long-term returns (i.e., playing reversal); or on the full-term structure of prior returns (i.e., playing combined momentum and reversal via a two-way sort) leads to significant value added relative to indexation.[15] Even better though is the performance of the mixed momentum/reversal strategy, which is conditional on market state (i.e., playing momentum in up markets and reversal in down markets).[16] From the beginning of the 1990s onwards, this strategy was able to consistently deliver cumulative returns higher than those of strategies that ignore the state of the market.

We have seen that momentum and reversal exist in Canada, and they are both conditional on market state. Specifically, momentum is stronger in up markets and reversal is stronger in down markets. Further, we have

FIGURE 1

SIMULATION OF A MIXED MOMENTUM/REVERSAL STRATEGY CONDITIONAL ON MARKET STATE



argued that these empirical regularities have reasonably firm psychological foundations. This matters, since the properly skeptical should consider whether data mining has occurred, or whether results rest on foundations that appear to have some degree of longevity. Still, why is it that psychologically unencumbered traders do not swoop in and arbitrage away these opportunities? To some extent this likely happens, but there seem to be limits. Aside from the fact that we are all human and subject to psychological influences, the limits to arbitrage argument (see Shleifer (2000)) suggests that arbitrage is a far from omnipotent force, primarily because of capital constraints facing arbitrageurs, along with the short-term career risks that they inevitably face. ▮

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ENDNOTES

1. Some view the use of this model as controlling for style more than a risk-adjustment.
2. In the latter paper, Japan proved to be the main exception.
3. Earlier work on Canadian momentum was undertaken by Foerster, Prihar and Schmitz (1994), Foerster (1996) and Kan and Kirikos (1996). Additionally, Cao and Wei (2002) looked at Canadian industry-level momentum.
4. One can only speculate on why momentum in Canada has been greater than in the U.S. Earnings momentum (which eventually translates into price momentum) may be specific to the disclosure rules of the country. The fact that the Canadian market is (a) less diversified (concentrated in a few sectors); and (b) of lower liquidity than the U.S. market could translate into higher excess returns, which may be difficult to explain by conventional risk-adjustment models (which assume well-diversified portfolios and investors not demanding any liquidity risk premia). Finally, behavioral factors (to be described later in the introduction) may vary from country to country.
5. Its disappearance in down markets (in the U.S. data) as documented by Cooper, Gutierrez and Hameed (2004) seems odd though. In Canada, more logically, momentum is only reduced, as shown in the subsequent section.
6. For details, see Deaves and Miu (2007).
7. Jegadeesh (1990) for the U.S., and Assoe and Sy (2003) for Canada, demonstrate short-term reversal. Boudoukh, Richardson and Whitelaw (1994) attribute this primarily to microstructure effects.
8. Besides having continuously valid return information over the full formation period, a firm needs to have valid book and market values at the beginning of the holding period in order to be eligible for consideration. Book and market values are also required in the construction of the Fama-French factors, which are used subsequently to adjust for risk. This was why we had to merge the two databases.
9. Results are robust to the use of other intervals. For details, see Deaves and Miu (2007).
10. For details, see Deaves and Miu (2007).
11. We repeat the analysis (results not reported) by defining market state based on 24-month and 36-month prior market returns to confirm the robustness of our conclusions.
12. The results are robust to changing interval length. For details, see Deaves and Miu (2007).
13. This cumulative return is tantamount to a cumulative portfolio value based on a $1 initial investment.
14. The use of terciles rather than quintiles allows us to ensure we have a sufficient number of stocks within each portfolio when we conduct the two-way sort.
15. For brevity we do not consider the important role of transaction costs. Deaves and Miu (2007) show however that while their consideration reduces profitability it does not eliminate it. One thing to keep in mind is that a cost-effective strategy will focus on more liquid stocks. When less liquid stocks are dropped, reversal, as a stand-alone strategy, actually does worse than momentum.
16. In rebalancing the portfolio composition every six months, the average turnover rate of the conditional mixed momentum/reversal strategy is 0.242, which is actually smaller than both of the unconditional momentum (0.244) and the unconditional two-way sort (0.271) strategies. Including transaction costs will therefore only enhance the benefit of using the conditional strategy over the two unconditional strategies. Nevertheless, in conducting the unconditional reversal strategy, the portfolio is only required to be turned over at an average rate of 0.141.