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The 52-week high and momentum investing in international stock indexes

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Abstract

A commonly held view is that short-term momentum and long-term reversals in returns are an integrated process [e.g., Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*, 307–343; Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and over-reaction. *Journal of Finance*, *53*, 1839–1886; Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance*, *54*, 2143–2184]. Recently, George and Hwang [George, T. J., & Hwang, C. (2004). The 52-week high and momentum investing. *Journal of Finance*, *59*, 2145–2176] strikingly find that momentum and reversals are largely separate phenomena. Due to the critical importance of this finding to theoretical asset pricing and practical investment decisions, we examine this issue in international stock markets. Differently from George and Hwang (2004), we find that their conclusions may be open to question because momentum and reversals co-exist in the international stock indexes.

JEL classification: G14; G15

Keywords: Momentum; Reversals; International stock markets

1. Introduction

There is substantial domestic and international evidence of stock momentum at short horizons, the case in which stocks that have performed well (poorly) in the recent past continue to perform

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well (poorly) in the future.[1] Jegadeesh and Titman (1993), Fama and French (1996), and Grundy and Martin (2001) show that risk adjustment, unconditional or conditional, tends to deepen rather than explain momentum.[2] Although Conrad and Kaul (1998) find evidence that momentum is explained by the cross-sectional dispersion in unconditional means (a proxy for expected returns),[3] Jegadeesh and Titman (2002) reject their claim and find that their results are driven by small sample bias.[4] Contrary to Chordia and Shivakumar (2002) who find that momentum can be explained by a set of lagged macroeconomic variables, Griffin, Ji, and Martin (2003) recently find that momentum has little relation to those macro variables.

There is also evidence that stock returns exhibit reversals at longer horizons.[5] Jegadeesh and Titman (1993) find that short-term momentum co-exists with long-term reversals. Motivated by these findings, Barberis, Shleifer, and Vishny (1998) (hereafter, "BSV"), Daniel, Hirshleifer, and Subrahmanyam (1998) ("DHS"), and Hong and Stein (1999) ("HS") propose behavioral models in which short-run undereaction (delayed overreaction) and long-run overreaction are sequential components of the same process by which investors react to information. BSV and DHS emphasize investor cognitive biases, while HS emphasize gradual information diffusion. Hong, Lim, and Stein (2000) and Lee and Swaminathan (2000) find evidence that is consistent with momentum being caused by slow information diffusion. Jegadeesh and Titman (2001) provide further evidence on the co-existence of short-term momentum and long-term reversals, Balvers and Wu (2006) show that combined momentum-contrarian strategies outperform both pure momentum and pure contrarian strategies.

Recently, George and Hwang (2004) propose a new explanation that focuses on an anchor-and-adjust bias. They argue that when good (bad) news has pushed a stock's price near (far from) the reference point (e.g. the 52-week high), investors are reluctant to bid the price higher (lower) even if the information warrants it. [6] But eventually investors correct the initial bias without overreaction. Two important empirical findings are that (1) nearness to the 52-week high dominates past returns in terms of predictive power and largely explains momentum profits, and (2) momentum profits do not reverse when past performance is measured by proximity to the 52-week high. These findings are of great importance. They challenge the behavioral models of BSV, DHS, and HS, because all these behavioral models stress that short-term momentum and long-term reversals are an integrated process.

Nevertheless, over the past 20 years, financial economists have looked at stock return predictability every which way. With so much searching, it is likely, purely by chance, that someone will uncover what looks to be patterns. There are several ways of addressing the data-mining issue. Perhaps the most robust is to perform an out-of-sample test. We take this approach and examine 52-week high momentum investing in international stock indexes. To see whether momentum is due to systematic risk in international stock markets, we adjust risk by the ICAPM, the two-factor model of Fama and French (1998), and the multi-factor models that explicitly take exchange-rate

[1] See Jegadeesh and Titman (1993), Rouwenhorst (1998), Chan, Hameed, and Tong (2000), Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), and Lewellen (2002).

[2] However, Du and Denning (2005) recently find that common risk based on a delayed-reaction model can largely explain industry momentum.

[3] Berk, Green, and Naik (1999) provide a theoretical model in which stocks with high (low) realized returns are those that have high (low) expected returns.

[4] Du and Boyce (2007) further find that sources of momentum are time varying.

[5] See DeBondt and Thaler (1985), Fama and French (1988), Poterba and Summers (1988), and Balvers, Wu, and Gilliland (2000).

[6] Theoretical models taking the same approach can be found in Klein (2001) and Grinblatt and Han (2002).

risk into account. Empirically, we find that the two-factor model of Fama and French (1998) performs relatively better. This probably is due to that the global market and value factors may already contain the information of exchange-rate risk. Thus, our discussion will mainly focus on the results based on the two-factor model. Nevertheless, our main empirical findings in this paper are generally robust to all benchmark models we use.

Consistent with George and Hwang (2004), we find that nearness to the 52-week high dominates past returns in terms of predictive power and largely explains momentum profits. That is, as soon as we control the effects of nearness to the 52-week high, risk-adjusted momentum profits based on past returns generally become insignificant. Outside of January, the mean risk-adjusted momentum profit based on past returns is 0.59% per month with a *t*-statistics of 3.14; however, as soon as the effects of nearness to the 52-week high are taken into account, it decrease to 0.21% per month with a *t*-statistics of only 1.13. The stock and currency transaction costs for the momentum strategies are substantial but erase 1/2 to 2/3 of the risk-adjusted profits. Thus, momentum strategies are profitable even after we adjust for risk and transaction costs. The dominance of nearness to the 52-week high supports the notion that the anchor-and-adjust bias may be a better description of investor behavior.

However, different from George and Hwang (2004), we find that short-run momentum co-exists with long-run reversals in international stock indexes even after risk adjustment. This is true for both the strategy based on past returns and the strategy based on nearness to the 52-week high. Hence, the notion that momentum and reversals are separate phenomena may be open to question. Our results suggest that investors may still overreact when they correct their initial bias. Intuitively, it is also unlikely that investors only underreact to information, but do not overreact.

The remainder of the paper is organized as follows: Section 2 describes the data and the empirical methodology. Section 3 investigates the predictive power of the 52-week high and past returns. Section 4 examines momentum and reversals. Section 5 concludes the manuscript.

2. Data and empirical methodology

Monthly data are obtained from Morgan Stanley Capital International (MSCI) for stock market price and gross price indexes of 18 developed markets.[7] The sample covers the period from December 1969 to July 2004. We use the price index in each market to construct nearness to the 52-week high. Gross price indexes that include reinvested gross dividends are used to compute returns. Following related studies (e.g., Balvers, Wu, & Gilliland, 2000), we focus on the indexes in dollar terms.[8] The summary statistics are reported in Table 1, with average monthly return and standard error for each country and each country's beta with the world index return.

In the tests that follow, we compare the momentum strategy of Jegadeesh and Titman (1993) (hereafter, "JT") to the strategy of George and Hwang (2004) (hereafter, "GH") that is based on nearness to the 52-week high for the international data. The goal is to examine whether nearness to

[7] These countries are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

[8] If we use home-currency returns, momentum results will be hard to interpret. Suppose (for simplicity) our December-2000 winner portfolio consists of US and Japan. The return for US index in US dollars is 3.09%, and that for Japan index in Japanese Yens is 7.61%. The winner-portfolio return computed as an average will be 5.35%. Since the returns are in different denominations, this average is difficult to interpret.

Table 1
Summary statistics of the county-index returns

Country	Mean return	Standard error	β with world index
Australia	0.0084	0.0451	0.92
Austria	0.0096	0.0539	0.88
Belgium	0.0090	0.0643	1.06
Canada	0.0089	0.0857	1.15
Denmark	0.0070	0.0727	1.01
France	0.0085	0.0587	0.49
Germany	0.0105	0.0554	0.83
HK	0.0078	0.0560	0.98
Italy	0.0103	0.0541	0.70
Japan	0.0089	0.0656	1.04
Netherlands	0.0081	0.0625	0.95
Norway	0.0125	0.1073	1.21
Singapore	0.0055	0.0735	0.83
Spain	0.0087	0.0645	1.02
Sweden	0.0105	0.0535	0.97
Switzerland	0.0090	0.0765	1.01
UK	0.0077	0.0653	0.87
US	0.0112	0.0688	1.03
World	0.0081	0.0422	1.00

This table shows the summary statistics for the 18 country indexes, with average monthly return and standard error for each country and each country's beta with the world index return.

the 52-week high can dominate past returns in terms of predictive power even in international stock markets. For brevity and ease of comparison, we focus on the commonly studied 6-month/6-month strategy skipping a month between the ranking and investment period.

For the JT strategy, at the beginning of each month t, stock indexes are ranked in ascending order on the basis of their returns during the past 6 months ($t-7$ to $t-2$). Based on their rankings, following GH, we form three portfolios. Stock indexes ranked in the top 1/3 of indexes constitute the winner portfolio, indexes in the bottom 1/3 constitute the loser portfolio, and the remaining 1/3 of indexes constitute the middle portfolio. These portfolios are equally weighted. The momentum strategy is to hold for 6 months a self-financing portfolio that goes long the winner and short the loser portfolios. To increase statistical power, overlapping portfolios are constructed.

The GH strategy is constructed in the same way except that stock indexes are ranked based on nearness to the 52-week high, $P_{i,t-2}/\text{high}_{i,t-2}$, where $P_{i,t-2}$ is the price of index i in the month $t-2$ and $\text{high}_{i,t-2}$ is the highest price of index i during the 12-month period that ends in the month $t-2$.

To see whether momentum is due to risk, we adjust raw momentum profits by our benchmark models. The risk-adjusted returns are estimated intercepts from these models. We first consider the ICAPM and the two-factor model of Fama and French (1998). We construct these models in the same fashion as Fama and French (1998). That is, we use the U.S. Treasury Bill rate as the risk-free rate and the MSCI World Index return as the global market return in the ICAPM; we then add the international value premium to construct the two-factor model. The US risk-free rate and the international value premium are downloaded from Kenneth French's website.

One potential drawback with the above models is that they may not take exchange-rate risk into account. We therefore augment the two-factor model of Fama and French (1998) by adding three exchange-rate-risk factors (hereafter, the five-factor model). The new factors are the excess returns on the assets that are perfectly correlated with the exchange rate fluctuations. For efficiency purpose, we follow Dumas and Solnik (1995) and De Santis and Gerard (1998), and focus on three major currencies: the German Mark, the Japanese Yen and the British Pound. To construct the exchange-rate-risk factors, we consider a zero-investment strategy: borrowing one US dollar at the US risk-free rate and investing in a foreign country's risk-free asset (e.g. the risk-free asset in Germany/Japan/UK). The dollar return in month t then is $s_{t-1}(1+i_t)/s_t$, where s_t is the nominal exchange rate (foreign currency/US dollar) at the end of month t, and i_t is the foreign risk-free rate in month t. Take the natural logarithm to obtain the continuous net return. To obtain the excess return on this zero-investment portfolio, we subtract the net return by the U.S. risk-free rate. Since our portfolio only contains the risk-free assets, the return on this investment will mostly reflect the exchange-rate risk. We obtain the monthly end-of-period exchange-rate data for the Mark, Yen, and Pound (Dollar is the base currency) from International Financial Statistics (IFS). We further use the appropriate IFS Treasury-bill rates as risk-free returns for Germany and the United Kingdom. For Japan we use IFS money market rates as the risk-free asset returns, because Treasury-bill rates are not available for Japan.

To see how well our benchmark models explain the index returns, we perform regression tests. We regress the excess returns of 18 country indexes on our factor variables. Table 2 reports the results. To save space, we only report Alphas and adjusted-R^2s.[9] If a pricing model is a good description of asset returns, we expect to see low Alphas and high adjusted-R^2s. It seems that the two-factor model performs better than the ICAPM. It generally produces higher adjusted-R^2s and similar or even smaller Alphas (in magnitude) than the ICAPM. Specifically, the average adjusted-R^2 is 42% for the two-factor model and 39% for the ICAPM; the average Alpha is −0.09% for the two-factor model and 0.11% for the ICAPM.

To examine whether the exchange-rate factors have additional explanatory power, we look at the five-factor model. Although it generates a slightly higher average adjusted-R^2 (44%) than the two-factor model (42%), it tends to produce much larger Alphas. For instance, the average Alpha is −0.09% based on the two-factor model, but it is −0.85% based on the five-factor model! Most exchange-rate-factor coefficients in the five-factor model are not significant: only 8 out of 54 coefficients are significant in the unreported results.

We also examine several alternative models with different combinations of the exchange-rate factors. To save space, we only report the results for the best-performing model in Table 2. This model includes the Fama-French two factors and the exchange-rate factor for German Mark (hereafter, the three-factor model). The model generates a same average adjusted-R^2 (42%) as the two-factor model. But it still produces much larger Alphas (−0.82%) than the two-factor model (−0.09%). Thus, it seems that adding the exchange-rate factors does not improve our model much. This probably is due to that the global market and value factors may already contain the information about exchange-rate risk.

Motivated by these findings, our discussion will mainly focus on the results based on the two-factor model. But we also provide the results based on the other models. It is important to note that our main empirical findings in this paper are robust to all four benchmark models.

[9] The unreported results are available upon request.

Table 2
Bench-mark model regressions

	ICAPM		Two-factor model		Five-factor model		Three-factor model	
	Alpha	$\bar{R}^2$	Alpha	$\bar{R}^2$	Alpha	$\bar{R}^2$	Alpha	$\bar{R}^2$
Australia	0.0006 (0.47)	0.74	0.0009 (0.63)	0.72	**0.0115** (3.98)	0.75	0.0049 (1.66)	0.72
Austria	0.0018 (0.91)	0.47	0.0004 (0.15)	0.49	**−0.0138** (−3.31)	0.51	−0.0092 (−1.59)	0.51
Belgium	0.0007 (0.34)	0.49	0.0013 (0.57)	0.50	**−0.0279** (−5.92)	0.61	−0.0016 (−0.51)	0.52
Canada	0.0003 (0.07)	0.32	−0.0042 (−1.07)	0.36	0.001 (0.14)	0.34	−0.0021 (−0.41)	0.34
Denmark	−0.0012 (−0.48)	0.34	−0.002 (−0.67)	0.34	−0.0028 (−0.52)	0.33	0.0002 (0.05)	0.33
France	0.002 (0.54)	0.12	−0.0028 (−0.69)	0.17	**−0.0252** (−3.41)	0.21	−0.0126 (−1.81)	0.20
Germany	0.0029 (1.18)	0.40	0.0009 (0.32)	0.41	**−0.0147** (−3.42)	0.43	−0.0072 (−1.17)	0.42
HK	−0.0003 (−0.15)	0.55	−0.0018 (−0.71)	0.53	0.004 (0.81)	0.54	0.0006 (0.12)	0.53
Italy	0.0031 (1.15)	0.30	0.0008 (0.30)	0.33	**−0.0145** (−2.35)	0.35	−0.005 (−0.99)	0.34
Japan	0.0006 (0.25)	0.45	0.0008 (0.28)	0.47	**−0.0108** (−2.06)	0.48	−0.0072 (−1.46)	0.48
Netherlands	0.0001 (0.05)	0.41	−0.0022 (−0.74)	0.44	**−0.0157** (−3.11)	0.46	**−0.0122** (−2.08)	0.46
Norway	0.0037 (0.81)	0.22	0.0008 (0.18)	0.27	0.001 (0.12)	0.26	0.006 (1.07)	0.26
Singapore	−0.0021 (−0.60)	0.23	−0.0019 (−0.50)	0.25	−0.0099 (−1.57)	0.25	0.0001 (0.02)	0.25
Spain	0.0005 (0.18)	0.44	−0.0013 (−0.43)	0.47	−0.0031 (−0.59)	0.59	−0.0046 (−1.01)	0.48
Sweden	0.0024 (1.59)	0.59	0.0015 (0.91)	0.62	**−0.0075** (−2.54)	0.61	−0.0016 (−0.34)	0.61
Switzerland	0.0008 (0.19)	0.31	−0.0051 (−1.23)	0.39	**−0.0214** (−3.62)	0.42	**−0.0116** (−2.31)	0.40
UK	0.0000 (0.00)	0.32	−0.003 (−0.94)	0.34	−0.0058 (−1.09)	0.35	−0.0031 (−0.94)	0.35
US	0.003 (1.11)	0.40	0.0016 (0.44)	0.42	0.0018 (0.25)	0.42	0.0011 (0.23)	0.42
Average		0.39		0.42		0.44		0.42

We regress the 18 country-index returns on our factor variables. This table reports the results. To save space, we only report Alphas and adjusted-R^2s. The values in parentheses are t-statistics. The t-statistics are based on Newey-West HAC estimates.

3. Momentum and 52-week high

3.1. Profitability of international momentum strategies

Table 3 reports average raw and risk-adjusted monthly returns of the JT and GH strategies. Table 3 also distinguishes between January and other calendar months. The returns to these strategies are very close. Outside of January, the average raw monthly return for the JT strategy is 0.69% per month with a t-statistic of 4.03, while that of the GH strategy is 0.62% per month with a t-statistic of 3.65. Momentum profits do not change much even we adjust them for risk based on our benchmark models. Outside of January, the two-factor model risk-adjusted mean returns are 0.59% per month (t-statistic = 3.14) for the JT strategy and 0.65% per month (t-statistic = 3.41) for the GH strategy. Our results are compatible with the findings of Jegadeesh and Titman (1993), Fama and French (1996) and Grundy and Martin (2001) for U.S. individual stocks in that risk adjustment does not explain momentum.

Table 3
Profits from momentum strategies

	JT strategy		GH strategy	
	Overall	Non-Jan	Overall	Non-Jan
Raw returns				
Mean	0.0069	**0.0069**	0.0055	**0.0062**
t-statistics	4.00	4.03	3.21	3.65
ICAPM risk adjusted returns				
Mean	0.0067	**0.0066**	0.0056	**0.0061**
t-statistics	3.85	3.81	3.19	3.49
Two-factor model risk-adjusted returns				
Mean	0.0059	**0.0059**	0.0057	**0.0065**
t-statistics	2.97	3.14	2.80	3.41
Five-factor model risk-adjusted returns				
Mean	0.0083	**0.0093**	0.0089	**0.0101**
t-statistics	2.10	2.29	2.55	2.72
Three-factor model risk-adjusted returns				
Mean	0.0085	0.0065	0.0079	**0.0072**
t-statistics	3.04	1.71	3.24	2.32

This table reports average monthly returns of the Jegadeesh and Titman (1993) (JT) and George and Hwang (2004) (GH) strategies. For JT strategy, at the beginning of each month t, stock indexes are ranked in ascending order on the basis of their returns during the past 6 months ($t-7$ to $t-2$). Those ranked in the top 1/3 of indexes constitute the winner portfolio, and those in the bottom 1/3 constitute the loser portfolio. These portfolios are equally weighted. The strategy is to hold for 6 months a self-financing portfolio that goes long the winner and short the loser portfolios. To increase statistical power, overlapping portfolios are constructed. The GH strategy is constricted in the same way except that indexes are ranked based on nearness to the 52-week high, $P_{i,t-2}/\text{high}_{i,t-2}$, where $P_{i,t-2}$ is the price of index i in the month $t-2$ and $\text{high}_{i,t-2}$ is the highest price of index i during the 12-month period that ends in the month $t-2$. The risk-adjusted returns are estimated intercepts from the ICAPM, the two-factor model of Fama and French (1998), the five-factor model, or the three-factor model. The t-statistics are based on Newey-West HAC estimates.

3.2. Transaction costs

Since most of the firms included in MSCI indexes are large firms (e.g., Fama & French, 1998), we can greatly mitigate the effects of small stocks, i.e. high stock trading costs.[10] However, following Balvers and Wu (2006), we still use a conservative estimate of 2% per switch to compute stock transaction costs.[11] In practice, to implement international momentum strategies, one will also incur currency transaction costs. Qi and Wu (2006) show that currency transaction costs are much lower than those for stocks. A conservative estimate is 0.08% per switch. Taken together, these studies suggest that a conservative estimate for total transaction costs is about 2.08% per switch.

The average risk-adjusted return (based on the two-factor model) for the JT strategy is 7.31% per year (or 0.59% per month). The JT strategy requires a switch 20% of the time, or 2.4 times per annum (for both winner and loser portfolios). The resulting transaction costs of 5% leave an excess return of 2.31% for the JT strategy. Similarly, the average risk-adjusted return (based on the two-factor model) for the GH strategy is 8.09% per year (or 0.65% per month). The GH strategy requires a switch 17% of the time, or 2.04 times per annum (for both winner and loser portfolios). The resulting transaction costs of 4.24% leave an excess return of 3.85% for the GH strategy. Therefore, both strategies are still profitable even after we adjust for risk and transaction costs. As Grundy and Martin (2001) point out, even if transaction costs preclude one from actually undertaking a momentum strategy profitably, this does not imply that momentum disappears, it is still an anomalous feature of financial markets.

3.3. Dominance of the 52-week high momentum strategy

The correlation between the profits from the two strategies is high, 84%. One possible explanation, suggested by GH, is that JT momentum profits are largely explained by the GH measure. In other words, nearness to the 52-week high dominates past returns in terms of predictive power. To examine this explanation, following GH, we perform two sets of tests.

The first test is a pair-wise nested comparison of profits from the GH strategy versus the JT strategy. Specifically, stock indexes are first collected into winner, middle, and loser groups using the JT (GH)'s ranking. We then implement the GH (JT) strategy within each group. The middle portfolios deserve special attention. The indexes in these portfolios are those that the first measure predicts will not have momentum or will have weak momentum. Thus, if momentum is mainly explained by the first measure, momentum profits should not be available in the middle portfolio by using the other measure. Otherwise, it implies that the other measure may have more predictive power. The results are presented in Table 4. Consistent with GH, we also find that the GH measure has more predictive power. Outside of January, within the middle group identified by the JT measure (Panel A), the GH strategy generates significant risk-adjusted profits based on the two-factor model (the mean is 0.38% per month with a *t*-statistics of 2.29); on the other hand, the JT strategy within the middle group identified by the GH measure (Panel B) is not profitable (the mean is 0.29% per month with a *t*-statistics of 1.71).

[10] This is important. As Lesmond, Schill, and Zhou (2004) show, momentum in U.S. individual stocks may not be profitable due to high stock trading costs caused by small stocks.

[11] A switch consists of selling one country index and purchasing another. There is therefore a round-trip transaction cost in the form of a brokerage cost, taxes, and the bid-ask spread.

Table 4
Predictive power of nearness to the 52-week high and past returns: pair-wise comparison

	Panel A: portfolios based on the JT measure					
	Winner		Middle		Loser	
	Overall	Non-Jan	Overall	Non-Jan	Overall	Non-Jan
Raw returns						
Mean	0.0011	0.0012	0.0023	**0.0031**	0.0030	0.0042
t-statistics	0.85	0.93	1.58	2.13	1.20	1.77
ICAPM risk-adjusted returns						
Mean	0.0013	0.0013	0.0023	**0.0031**	0.0033	0.0044
t-statistics	1.01	1.00	1.57	2.06	1.33	1.85
Two-factor model risk-adjusted returns						
Mean	0.0015	0.0017	0.0031	**0.0038**	0.0025	0.0039
t-statistics	1.07	1.22	1.93	2.29	0.93	1.52
Five-factor model risk-adjusted returns						
Mean	−0.0036	−0.0041	0.0102	**0.0118**	0.0023	0.0038
t-statistics	−1.18	−1.24	4.92	**5.08**	0.54	0.93
Three-factor model risk-adjusted returns						
Mean	0.0002	−0.0006	0.0039	**0.0062**	0.0014	0.0030
t-statistics	0.13	−0.23	2.45	**3.32**	0.41	0.83

	Panel A: portfolios based on the GH measure					
	Winner		Middle		Loser	
	Overall	Non-Jan	Overall	Non-Jan	Overall	Non-Jan
Raw returns						
Mean	0.0028	0.0023	0.0046	**0.0038**	0.0059	0.0060
t-statistics	1.70	1.44	3.27	2.59	2.23	2.22
ICAPM risk-adjusted returns						
Mean	0.0025	0.0020	0.0044	**0.0036**	0.0060	**0.0060**
t-statistics	1.58	1.36	3.10	2.49	2.26	2.22
Two-factor model risk-adjusted returns						
Mean	0.0020	0.0017	0.0036	0.0029	0.0040	0.0042
t-statistics	1.51	1.24	2.29	1.71	1.37	1.41
Five-factor model risk-adjusted returns						
Mean	−0.0021	−0.0015	0.0054	**0.0065**	−0.0025	−0.0026
t-statistics	−0.66	−0.47	1.89	**2.25**	−0.49	−0.52
Three-factor model risk-adjusted returns						
Mean	0.0032	0.0019	0.0056	0.0050	0.0033	0.0018
t-statistics	1.91	0.77	2.70	1.69	0.97	0.45

Stock indexes are first collected into winner, middle, and loser groups using the JT (GH)'s rankings. We then implement the GH (JT) strategy within each group. Panel A reports the average monthly returns that are long GH winners and short GH losers within winner, middle, and loser portfolios identified by the JT measure. Panel B reports the average monthly returns that are long JT winners and short JT losers within winner, middle, and loser portfolios identified by the GH measure. The risk-adjusted returns are estimated intercepts from the ICAPM, the two-factor model of Fama and French (1998), the five-factor model, or the three-factor model. The *t*-statistics are based on Newey-West HAC estimates.

Table 5
Predictive power of nearness to the 52-week high and past returns: regression analysis

	Intercept	$r_{i,t-1}$	JTW	JTL	GHW	GHL	JTW-JTL	GHW-GHL
Overall								
Raw returns	0.0095 (3.57)	0.0382 (1.92)	0.0007 (0.71)	−0.0037 (−2.93)	0.0018 (2.10)	−0.0011 (−0.94)	0.0044 (2.60)	0.0030 (1.82)
ICAPM	0.0066 (4.40)	0.0376 (1.86)	0.0005 (0.56)	−0.0037 (−2.82)	0.0019 (2.20)	−0.0011 (−0.93)	0.0043 (2.50)	0.0031 (1.86)
Two-factor model	0.0052 (2.75)	0.0354 (1.65)	−0.0001 (−0.06)	−0.0026 (−1.84)	0.0025 (2.50)	−0.0015 (−1.16)	0.0025 (1.45)	0.0039 (2.24)
Five-factor model	0.0035 (0.87)	−0.0315 (−0.74)	0.0018 (0.69)	−0.0011 (−0.44)	0.001 (0.50)	−0.0069 (−3.58)	0.0028 (0.83)	0.0080 (2.99)
Three-factor model	0.0039 (1.67)	0.0478 (1.52)	0.0011 (0.84)	−0.004 (−2.20)	0.0015 (1.28)	−0.0018 (−1.36)	0.0051 (2.03)	0.0033 (1.92)
Non-Jan								
Raw returns	0.0095 (3.51)	0.026 (1.36)	−0.0001 (−0.11)	−0.0041 (−3.03)	0.0019 (2.20)	−0.0022 (−1.60)	**0.0040** (2.24)	**0.0041** (2.33)
ICAPM	0.0073 (4.84)	0.0257 (1.33)	−0.0003 (−0.28)	−0.0041 (−2.91)	0.0019 (2.24)	−0.0021 (−1.56)	**0.0038** (2.12)	**0.0041** (2.29)
Two-factor model	0.006 (3.07)	0.0212 (1.03)	−0.0008 (−0.90)	−0.0029 (−2.09)	0.0024 (2.47)	−0.0026 (−1.83)	0.0021 (1.13)	**0.0050** (2.69)
Five-factor model	0.0017 (0.41)	−0.0336 (−0.85)	0.0023 (0.90)	0.0004 (0.19)	0.0011 (0.54)	−0.0091 (−3.83)	0.0019 (0.56)	**0.0102** (3.39)
Three-factor model	0.0037 (1.24)	−0.0072 (−0.24)	0.0017 (0.85)	−0.0024 (−1.04)	0.0015 (1.13)	−0.0037 (−2.23)	0.0040 (1.19)	**0.0053** (2.42)

Each month, 6 (j=2, ……, 7) cross-sectional regressions of the following form are estimated, $r_{i,t} = b_{ojt} + b_{1jt} r_{i,t-1} + b_{2jt}\mathrm{JTW}_{i,t-j} + b_{3jt}\mathrm{JTL}_{i,t-j} + b_{4jt}\mathrm{GHW}_{i,t-j} + b_{5jt}\mathrm{GHL}_{i,t-j} + e_{i,t}$, where $r_{i,t}$ is the return of index i in month t, $\mathrm{JTW}_{i,t-j}$ is equal to one if index i's past performance over the 6 month period ($t-j-6$, $t-j$) is in the top 1/3 when measured by the JT measure, and is zero otherwise; $\mathrm{JTL}_{i,t-j}$ is equal to one if index i's past performance over the 6 month period ($t-j-6$, $t-j$) is in the bottom 1/3 when measured by the JT measure, and is zero otherwise. The variables $\mathrm{GHW}_{i,t-j}$ and $\mathrm{GHL}_{i,t-j}$ are defined similarly for the GH strategy. The return in month t of the set of pure winner or pure loser portfolios can be expressed as: $\mathrm{JTW}_t = 1/6\sum_{j=2}^{7} b_{2jt}$, $\mathrm{JTL}_t = 1/6\sum_{j=2}^{7} b_{3jt}$, $\mathrm{GHW}_t = 1/6\sum_{j=2}^{7} b_{4jt}$, and $\mathrm{GHL}_t = 1/6\sum_{j=2}^{7} b_{5jt}$, where the individual coefficients are computed from separate cross-sectional regressions for each j. The time-series averages of the month-by-month estimates of these average and the risk-adjusted returns, and associated t-statistics are reported in this table. The risk-adjusted returns are estimated intercepts from the ICAPM, the two-factor model of Fama and French (1998), the five-factor model, or the three-factor model. The t-statistics are based on Newey-West HAC estimates.

To examine these two strategies simultaneously, we also follow GH and implement a regression approach based on Fama and MacBeth (1973). We estimate the contributions of the various overlapping portfolios formed in month $t-j$ to the month t return in the same fashion as GH. Specifically, we estimate the following regression model:

$$\begin{aligned} r_{i,t} &= b_{ojt} + b_{1jt} r_{i,t-1} + b_{2jt}\,\mathrm{JTW}_{i,t-j} + b_{3jt}\,\mathrm{JTL}_{i,t-j} \\ &\quad + b_{4jt}\,\mathrm{GHW}_{i,t-j} + b_{5jt}\,\mathrm{GHL}_{i,t-j} + e_{i,t} \end{aligned} \tag{1}$$

where $r_{i,t}$ is the return of Index i in month t, $\mathrm{JTW}_{i,t-j}$ is equal to one if index i's past performance over the 6 months period $(t-j-6, t-j)$ is in the top 1/3 when measured by the JT measure, and is zero otherwise; $\mathrm{JTL}_{i,t-\mathrm{j}}$ is equal to one if index i's past performance over the 6 months period $(t-j-6, t-j)$ is in the bottom 1/3 when measured by the JT measure, and is zero otherwise. The variables $\mathrm{GHW}_{i,t-j}$ and $\mathrm{GHL}_{i,t-j}$ are defined similarly for the GH strategy. The month $t-1$ return $r_{i,t-1}$ is included to mitigate the impact of bid-ask bounce on the coefficient estimates.

Returns to 6 months/6 months strategy involve 6 overlapping portfolios formed over past 6 months. As GH show, the return in month t of the set of pure winner or pure loser portfolios can be expressed as averages $1/6\sum_{j=2}^{7} b_{2jt}$, $1/6\sum_{j=2}^{7} b_{3jt}$, $1/6\sum_{j=2}^{7} b_{4jt}$, and $1/6\sum_{j=2}^{7} b_{5jt}$, where the individual coefficients are computed from separate cross-sectional regressions for each $j=2$, ..., 7. The time-series averages of the month-by-month estimates of these averages together with the risk-adjusted returns, and associated t-statistics are reported in Table 5. The average profit that is related exclusively to each of the different momentum strategies can be calculated as the difference between the winner and loser profits. Consistent with GH, we find that as soon as the effects of the GH measure are taken into account, the JT measure loses its explanatory power. Outside of January, the GH strategy still generates significant risk-adjusted profits (based on the two-factor model) even with the presence of the JT measure: the mean is 0.50% per month with a t-statistics of 2.69. However, outside of January, the JT strategy is not profitable any more with the presence of the GH measure: the average risk-adjusted profit (based on the two-factor model) is 0.21% per month with a t-statistics of 1.13. Thus, the evidence suggests that momentum is largely explained by nearness to the 52-week high.

The results from the pair-wise comparisons and regression analysis support the idea that the anchor-and-adjust bias may be a better description of investor behavior. As a result, the models in Klein (2001) and Grinblatt and Han (2002) may deserve more attention.

4. Long-term reversals

GH find that nearness to the 52-week high dominates past returns in terms of predictive power and long-term reversals do not occur when past performance is based on nearness to the 52-week high in the US data. We have found that nearness to the 52-week high does dominate past returns in terms of predictive power for the international data. This raises a natural question. That is whether long-term reversals occur when past performance is based on nearness to the 52-week high in the international data. Following Jegadeesh and Titman (2001), we examine the returns of the momentum portfolio in the post-holding period up to five years. Fig. 1 presents the time Line. We do not use the regression approach as in GH. The reason is that we only have 18 stock indexes, and consequently, cross-sectional regressions may be imprecise.

Fig. 2 presents cumulative momentum profits for the JT and GH strategies. JT is the cumulative profit for the JT strategy. The cumulative profit in Month m, JT_m is computed as the sum of the average momentum profits from Month 0 to Month m. That is $\mathrm{JT}_m = \sum_{\tau=0}^{m} \overline{\mathrm{WML}}_{t+\tau}^{\mathrm{JT}}$, where

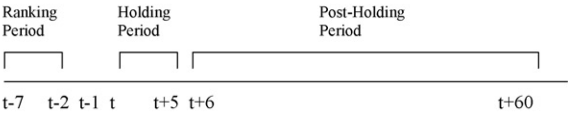

Fig. 1. Time line. (The 52-week High and Momentum Investing in International Stock Indexes, Ding Du.) At the beginning of each month t, stock indexes are ranked in ascending order on the basis of their performance during the past 6 months ($t-7$ to $t-2$). Those ranked in the top 1/3 of indexes constitute the winner portfolio, and those in the bottom 1/3 constitute the loser portfolio. The momentum strategy is to hold for 6 months (t to $t+5$) a self-financing portfolio that goes long the winner and short the loser portfolios. The post-holding period is from $t+6$ to $t+60$.

$\overline{\mathrm{WML}}_{t+\tau}^{\mathrm{JT}}$ is the average momentum profit for Month $t+\tau$ and $m=0, 1, \ldots\ldots, 60$. GH is cumulative profits for the GH strategy. It is computed in the same way.

Consistent with JT and GH, we find reversals in the JT momentum profits. Cumulative profits increase monotonically until they reach 2.98% at the end of Month 7. From Month 8, cumulative profits monotonically decrease until they become −5.37% at the end of Month 60. However, different from GH, we also find reversals in the GH momentum profits. Although initial reversals are weaker than the JT profits (the cumulative profit curve for GH strategy is very flat from Month 8 to 18), cumulative profits still reach −4.09% at the end of Month 60.

If investors overreact to information, both winners and losers should exhibit reversals. We therefore further look at the reversals in winner and loser portfolio returns. Specifically, we look at the average returns for winner and loser portfolios in the post-holding period up to five years in Fig. 3. In Panel A, we examine reversals in winner and loser portfolio returns identified by the past returns (the JT strategy). JTWIN is the average return of the winner portfolio identified by the JT strategy, while JTLOSE is the average return of the loser portfolio identified by the

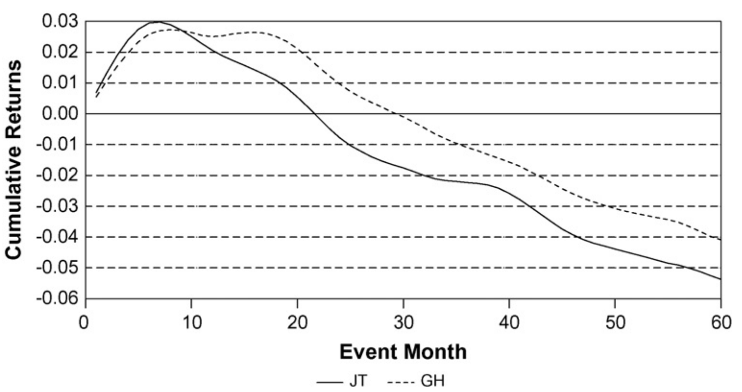

Fig. 2. Cumulative momentum profits. (The 52-week High and Momentum Investing in International Stock Indexes, Ding Du.) At the beginning of each month t, stock indexes are ranked in ascending order on the basis of their performance during the past 6 months ($t-7$ to $t-2$). Those ranked in the top 1/3 of indexes constitute the winner portfolio, and those in the bottom 1/3 constitute the loser portfolio. The momentum strategy is to hold for 6 months (t to $t+5$) a self-financing portfolio that goes long the winner and short the loser portfolios. The post-holding period is from $t+6$ to $t+60$. This graph presents cumulative momentum profits for the JT and GH strategies from t to $t+60$. JT is cumulative profits for the JT strategy. The cumulative profit in Month m, JT_m is computed as the sum of the average momentum profits from Month 0 to Month m. That is $\mathrm{JT}_m = \sum_{\tau=0}^{m} \overline{\mathrm{WML}}_{t+\tau}^{\mathrm{JT}}$, where $\overline{\mathrm{WML}}_{t+\tau}^{\mathrm{JT}}$ is the average momentum profit for Month $t+\tau$ and $m=0$, 1, ..., 60. GH is cumulative profits for the GH strategy. It is computed in the same way.

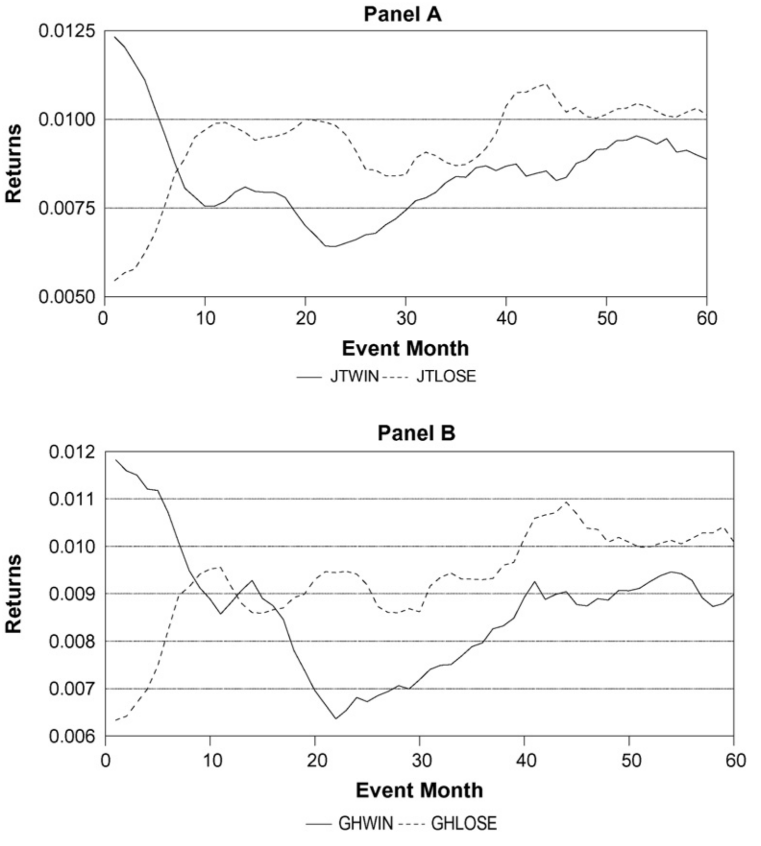

Fig. 3. Average returns of the winner and loser portfolios. (The 52-week High and Momentum Investing in International Stock Indexes, Ding Du.) At the beginning of each month t, stock indexes are ranked in ascending order on the basis of their performance during the past 6 months ($t-7$ to $t-2$). Those ranked in the top 1/3 of indexes constitute the winner portfolio, and those in the bottom 1/3 constitute the loser portfolio. The momentum strategy is to hold for 6 months (t to $t+5$) a self-financing portfolio that goes long the winner and short the loser portfolios. The post-holding period is from $t+6$ to $t+60$. This graph presents average returns for winner and loser portfolios. JTWIN is the average return of the winner portfolio identified by the JT strategy, while JTLOSE is the average return of the loser portfolio identified by the JT strategy. GHWIN is the average return of the winner portfolio identified by the GH strategy, while GHLOSE is the average return of the loser portfolio identified by the GH strategy.

JT strategy. Both the winner and loser portfolios exhibit reversals. For the winner portfolio, the average return in Month 0 is 1.23%. It decreases to 0.89% at the end of Month 60. For the loser portfolio, the average return in Month 0 is 0.55%. It increases to 1.01% at the end of Month 60.

In Panel B, we examine reversals in winner and loser portfolio returns identified by the GH strategy. GHWIN is the average return of the winner portfolio identified by the GH strategy, while GHLOSE is the average return of the loser portfolio identified by the GH strategy. The winner and loser portfolios also exhibit similar reversals. For the winner portfolio, the average return in Month 0 is 1.18%. It decreases to 0.90% at the end of Month 60. For the loser portfolio, the average return in Month 0 is 0.63%. It increases to 1.01% at the end of Month 60.

Fig. 4 depicts the risk-adjusted cumulative momentum profits. As we can see, even after risk adjustment, there are still reversals in both JT and GH momentum profits. The results do not depend on which benchmark model we use to adjust for the risk. Hence, the evidence suggests that the notion that they are separate phenomena may be open to question.

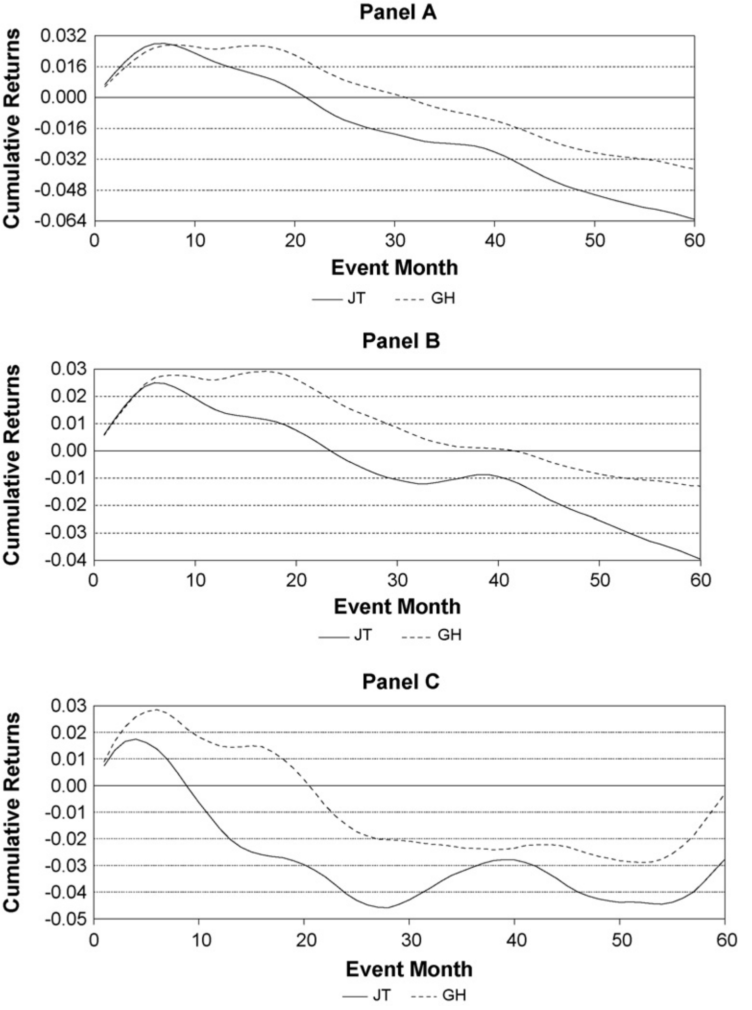

Fig. 4. Risk-adjusted cumulative momentum profits. (The 52-week High and Momentum Investing in International Stock Indexes, Ding Du.) At the beginning of each month t, stock indexes are ranked in ascending order on the basis of their performance during the past 6 months ($t-7$ to $t-2$). Those ranked in the top 1/3 of indexes constitute the winner portfolio, and those in the bottom 1/3 constitute the loser portfolio. The momentum strategy is to hold for 6 months (t to $t+5$) a self-financing portfolio that goes long the winner and short the loser portfolios. The post-holding period is from $t+6$ to $t+60$. This graph presents risk-adjusted cumulative momentum profits for the JT and GH strategies from t to $t+60$. JT is risk-adjusted cumulative profits for the JT strategy. GH is risk-adjusted cumulative profits for the GH strategy. The risk-adjusted returns are estimated intercepts from the ICAPM, the two-factor model of Fama and French (1998), the five-factor model, or the three-factor model. Panel A: ICAPM risk-adjusted cumulative momentum profits; Panel B: two-factor model risk-adjusted cumulative momentum profits; Panel C: five-factor model risk-adjusted cumulative momentum profits; Panel D: three-factor model risk-adjusted cumulative momentum profits.

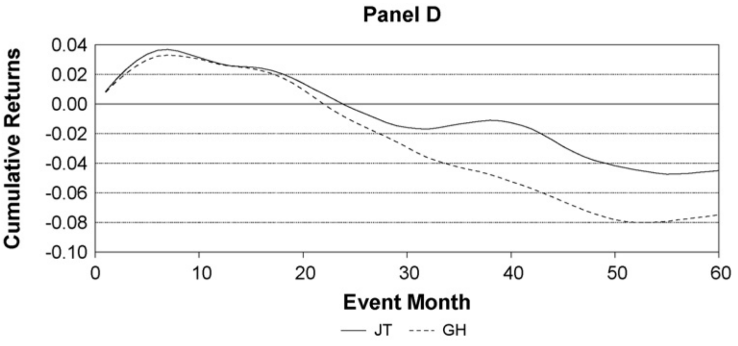

Fig. 4. (*Continued*).

5. Conclusion

Market efficiency implies that stock prices follow random walks, and returns are unpredictable. A voluminous literature has developed to test this hypothesis for its important implications for many of the paradigms used in financial economics. Contrary to the early supporting evidence surveyed in Fama (1970), there is evidence that stock prices do not follow random walks and returns are predictable. Jegadeesh and Titman (1993) document short-run momentum in stock returns, while DeBondt and Thaler (1985) discover long-run reversals. Motivated by these findings, Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) have developed behavioral models to account for both the short-term momentum and long-term reversals.

Recently, George and Hwang (2004) find that momentum is largely explained by an anchor-and-adjust bias where the anchor is the 52-week high of the stock price, and momentum and reversals are largely separate phenomena. The implication of these findings is of great importance, because they indicate a model with an anchor-and-adjust bias may be more tractable to describe investor behavior and investors do not overreact when they adjust.

To see whether their findings are sample specific, we perform similar tests as George and Hwang (2004) with the MSCI county indexes. The behavioral models are usually driven by firm-specific risk, while this paper uses the country portfolios with firm-specific risk generally eliminated. However, it is important to note that although a country portfolio does not have firm-specific risk, it still has country-specific idiosyncratic risk. Therefore, the basic logic of the behavioral models may still apply.[12] For instance, when a country's market has experienced extreme movements or is near (far from) its 52-week high (while the global market has been quite), there may be more uncertainty regarding whether or not this market has fully incorporated information. As a result, investor underreaction may be particularly strong.

Empirically, we find that international momentum strategies are profitable even after risk and transaction-cost adjustments. Furthermore, although nearness to the 52-week also dominates past returns in terms of predictive power in international stock markets, reversals do occur to both the momentum profits from the JT strategy and those from the GH strategy. Taken together, these findings suggest that an anchor-and-adjust bias may be a better description of investor behavior,

[12] Motivated by this reasoning, Balvers et al. (2000) examine mean reversion in the global market with the same MSCI county indexes.

but investors do overreact when they adjust. Intuitively, it is also unlikely that investors only underreact to information, but do not overreact.

Acknowledgements

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