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Contribution of 52-week low to the momentum strategy on 52-week high

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CONTRIBUTION OF 52-WEEK LOW TO THE MOMENTUM STRATEGY ON 52-WEEK HIGH

by

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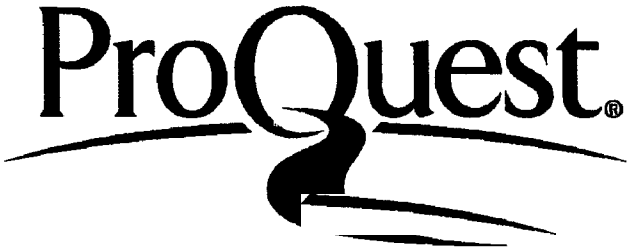

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ABSTRACT

I examine whether the momentum strategy based on 52-week high price can use 52-week low price as another reference point. I find that the remoteness of current price from 52-week low price plays an incremental role in the momentum profits of the strategy based on 52-week high price. Furthermore, I find that the role depends on the level of the nearness to 52-week high price. I find that the profits of the 52-week high price momentum strategy that also uses remoteness of current price from 52-week low price increase as the level of the nearness to 52-week high price increases. I also find that the profits of this strategy based on both 52-week high price and 52-week low price come largely from small stocks as the profits of the traditional momentum strategy is known to come largely from small stocks.

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Author Hyun Chul Cho

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TABLE OF CONTENTS

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

Jegadeesh and Titman (1993) published the seminal paper on the existence of momentum in stock returns. They show that the self-financing strategy of long winner stocks and short loser stocks in previous periods show positive returns in the holding period returns. Since their work, many other researchers have found stock return momentum in different samples[1].

With regard to the causes of these momentum phenomena, there have been efforts through some researchers to find them[2]. One of them is George and Hwang (2004). George and Hwang (2004) claim that the nearness of current price to 52-week high price (52-week high, hereafter) explains the large portion of momentum profits.

According to George and Hwang (2004), traders use the 52-week high as a reference point against which they evaluate the potential impact of news. When good news has pushed a stock's price near or to a new 52-week high, traders are reluctant to bid the price of the stock higher even if the information warrants it and the information

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[1] Among those are Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Lee and Swaminathan (2000), Griffin et al. (2003), Grundy and Martin (2001), and Antoniou et al. (2007). Jegadeesh and Titman (2001) also use out-of-sample to test the phenomena and find the momentum.

[2] Among those are Shefrin and Statman (1985), Barberis, Shleifer, and Vishny (1998), Daniel et al. (1998), Hong and Stein (1999), and Grinblatt and Han (2005).

eventually prevails and the price moves up, resulting in a continuation. When bad news pushes a stock's price far from its 52-week high, traders are initially unwilling to sell the stock at prices that are as low as the information implies and the information eventually prevails and the price falls. With these hypotheses, they show that the self-financing strategy using nearness to 52-week high earns significant profits in holding periods and explains the large portion of the profits of the simple momentum strategy which use past returns for winner (loser) portfolio formation.

As George and Hwang (2004) mention, the remarkable characteristic of the 52-week high is that it is a readily available piece of information making itself a reference point for investors. However, every newspaper and media which publishes 52-week high also publishes 52-week low price (52-week low, hereafter). This means that 52-week low is also a readily available piece of information and investors can use it as a reference point for their investments.

It seems that the reason why investors are reluctant to bid for the stocks near 52-week high is that the investors seem to feel the stock price has risen too high to buy. However, if the investors also have the information of 52-week low, the information would affect the investors determining whether the current stock price has risen a lot compared to the 52-week low.

Therefore, it seems presumable that even among the stocks with equivalent nearness to 52-week high the stocks far from 52-week low would give more fear to investors than the stock close to 52-week low because the investor would feel the former has risen a lot from its lowest price while they feel the latter has not risen much

considering the lowest price (52-week low). For instance, if the price of stock A is currently $50 and its 52-week high is $51, and its 52-week low is $10, then the potential investor would think the price of stock A has risen a lot and would feel fear to buy the stock. However, if the price of stock B is currently $50 and its 52-week high is still $51, but its 52-week low is $49, then even though the stock B's price has the same nearness to its 52-week high as the price of the stock A, the potential investor wouldn't feel that the stock B has risen a lot and wouldn't feel fear to buy the stock. Therefore, in the former case, the reduced demand for the stock A, which does not reflect true fundamental value of the stock, would bring momentum profits to the rational investors who buy the stock regardless of the 52-week low and in the latter case the demand for stock B would not be reduced reflecting true fu. ntal value of the stock and causing no momentum profits to investors.

With this mechanism working, if I group stocks into several groups based on their nearness to 52-week high from the lowest nearness to the highest nearness, there seems to be some differences in the investors' reluctance to bid the stocks between these groups. For the stocks in the high nearness to 52-week high group, investors might be more sensitive to the stock's 52-week low than for the stocks in the low nearness to 52-week high group. Investors could feel fear about the stocks in the high nearness to 52-week high group and be sensitive to the 52-week low and this high sensitivity to the remoteness from 52-week low could lead to great momentum return differences between the low remoteness from 52-week low and the high remoteness from 52-week low stocks in that high nearness to 52-week high group. However, they might not feel fear and not care a lot about the stocks in the low nearness to 52-week high group and not be so sensitive to the

52-week low. This possibility could result in differences in the role of the remoteness from 52-week low between the groups with different level of the nearness to 52-week high. I test this possibility in this study and the first hypothesis can be described as follows:

Hypothesis 1: The effect in the momentum returns produced by the change in the remoteness of current price from 52-week low depends on the level of the nearness of current price to 52-week high.

I form 25 portfolios based on the nearness of current price to 52-week high (GH1, hereafter) and the remoteness of current price from 52-week low (GH2, hereafter). I sort the stocks into five groups based on GH1 first and within the group I sort the stocks into five portfolios based on GH2 resulting 25 portfolios. If the returns of the self-financing portfolios based on GH2 within the equivalent GH1 are different among the different GH1 groups, then it can be said that the roles of GH2 are different depending on the level of GH1 confirming the possibility above.

The test results show that within the equivalent GH1 group the return of the portfolio based on GH2 increases as the GH2 increases meaning the incremental role of the remoteness from 52-week low to the momentum strategy based on the nearness to 52-week high. In the highest GH1 group, the GH2 portfolio returns increase from 1.00% to 1.78% per month and the second highest GH1 group, GH2 portfolio returns increase from 1.06% to 1.59% per month. The rest of the GH1 groups also show increases in GH2 portfolio returns.

The test results also show that the return differences between the lowest GH2 and the highest GH2 portfolio increase almost monotonically and consistently from the lowest GH1 group to the highest GH1 group. They i ease from 0.02% per month for the lowest GH1 group to 0.18%, 0.42%, 0.48%, and 0.69% per month for the highest GH1 group. This means that the impact of the remoteness of current price from 52-week low is different depending on the level of the nearness of current price to 52-week high and the impact is more positive as the level of the nearness of current price to 52-week high increases.

Hong et al. (2000) and Jegadeesh and Titman (2001) find that that momentum profits come largely from smaller stocks. Hong et al. (2000) find that once one moves past the very smallest capitalization stocks the profitability of momentum strategies declines sharply with market capitalization. Jegadeesh and Titman (2001) look at the characteristics of the momentum portfolios and they use "size" as a characteristic of the portfolio. Their portfolios show that both winners and losers tend to be smaller in size than the average stock in the sample.

If the stocks far from 52-week low give more momentum profits than the stocks close to 52-week low among the stocks with equivalent nearness to 52-week high and investors are more sensitive to the stock's 52-week low for the stocks in the high nearness to 52-week high group than for the stocks in the low nearness to 52-week high group then it is possible to build self-financing portfolio using both 52-week high and 52-week low on double sorting method. The self-financing portfolio longs the stocks with both the highest nearness to 52-week high and the highest remoteness from 52-

week low and shorts the stocks with both the lowest nearness to 52-week high and the lowest remoteness from 52-week low.

If size matters in the momentum profits as prior studies show, the momentum profits of this portfolio can also be affected by stock size. In other words, the large portion of momentum profits of the strategy built on both the nearness to 52-week high and the remoteness from 52-week low can arise in small size stocks. Therefore, I test the following hypothesis:

Hypothesis 2: Momentum profit of the strategy considering both 52-week high and 52-week low is more prominent in small size stocks than that in large size stocks.

To test this hypothesis, I first group the stocks in the sample into three groups based on their size. And then, I make 25 portfolios for each size group based on the GH1 and GH2 double sorts and examine the returns of the self-financing strategy of the extreme portfolios that longs the stocks with the highest GH1 and the highest GH2 and shorts the stocks with the lowest GH1 and the lowest GH2.

The test results show that the large portion of momentum profits of the strategy come from small size stocks. The small stock self-financing strategy of the extreme portfolios produces 1.39% monthly return on average and the large stock self-financing strategy of the extreme portfolios produces 0.81% monthly return on average.

I use common stocks in NYSE, AMEX, and NASDAQ from 1965 to 2013 to test the hypotheses. I use data from CRSP.

In the tests of Jegadeesh and Titman (2001) on momentum strategy, they exclude all stocks priced below $5 and all stocks with market capitalization that would place them in the smallest NYSE decile. They exclude these stocks to ensure that the results are not driven primarily by small and illiquid stocks or by bid-ask bounce. Excluding these stocks is known to be common standards in momentum studies that ensure that the test results are not driven by illiquid and unfrequently traded securities. Following this spirit, I use the data that excludes the stocks priced below $5 and the stocks that would be in the smallest NYSE decile. However, for the robustness purpose, I test the main hypothesis with the data that includes those stocks.

The robustness test results confirm the main hypothesis showing the incremental role of GH2 to the momentum strategy on GH1 and the role grows as the GH1 level increases from the 0.07% per month of the lowest GH1 group to 0.74% per month of the highest GH1 group.

The remainder of the paper is organized as follows: Chapter 2 describes the data and methodology. Chapter 3 describes the results of the analyses and Chapter 4 provides conclusions developed from the study.

CHAPTER TWO

DATA AND METHODOLOGY

I use all the NYSE, AMEX, and NASDAQ common stocks over the period from 1965 to 2013 included in CRSP. I exclude the stocks priced less than $5 or the stocks that would fall in the smallest NYSE decile at the end of the portfolio formation month.

I follow George and Hwang (2004) to make the measure for the nearness of current price to 52-week high (GH1) and the measure for the remoteness of current price from 52-week low (GH2) as follows:

$$\text{Measure for nearness of current price to 52-week high} = \frac{\textit{Current Price}}{\textit{52 week high price}},$$

$$\text{Measure for remoteness of current price from 52-week low} = \frac{\textit{Current Price}}{\textit{52 week low price}}.$$

The 52-week high price of a stock is the highest closing price of the stock during the past 365 days. The current price is the closing price of the stock at the end of the portfolio formation month. The prices are adjusted for distributions such as stock splits and dividends following CRSP.

Before the test of main hypothesis of this study that examines whether or not remoteness from 52-week low (GH2) would make a difference among the groups with the different level of the nearness to 52-week high (GH1), I first check if the remoteness

of current price from 52-week low has incremental impact on the momentum portfolios based on the nearness of current price to 52-week high. I use nested sorts on GH1 and GH2 for this test. I first rank the stocks on GH1 and group them into five quintiles and within each quintile I rank the stocks on GH2 and group the stocks into five quintile portfolios which results in 25 portfolios. The 25 portfolios are held for six months. I skip one month from the ranking month to avoid some of the bid-ask spread, price pressure, and lagged reaction effects that are shown in Jegadeesh (1990) and Lehmann (1990). I compute equally weighted returns and average the returns across the six months for each portfolio. I focus on the holding period returns of the self-financing portfolio formed on GH2 in each GH1 group. The self-financing portfolio longs the stocks in the quintile farthest from 52-week low and shorts the stocks in the quintile closest to 52-week low in the equivalent GH1 group. If the returns of the self-financing portfolios of the groups are statistically significant, then it can be said that the remoteness of current price from 52-week low plays incremental role to the momentum strategy based on the nearness of current price to 52-week high.

Though dependent sorts test allows us to find whether GH2 has significant influence on the momentum strategy based on GH1, it cannot show clearly whether GH2 make a difference among different GH1 groups. The difference in GH2 between the lowest GH2 portfolio and the highest GH2 portfolio within a GH1 quintile which leads to return differnces between the two portfolios could be quite different across the different GH1 quintiles, hence, the return differences among the different GH1 quintiles could result from different changes in GH2. I need the same change in GH2 to compare and examine the GH2 roles in different GH1 groups. To tackle this issue I use independent

sorts. I independently sort the stocks into five groups based on GH1 and GH2 and examine the returns to the resulting 25 portfolios. I first rank the stocks based on their GH1 and group them into five quintiles and within each quintile I sort the stocks based on GH2 into five portfolios. I look at the holding period returns of the self-financing portfolio formed on GH2 in each GH1 group. The self-financing portfolio longs the stocks of the highest GH2 portfolio and shorts the stocks of the lowest GH2 portfolio in the GH1 group. Here, the five self-financing portfolios long the stocks with similar high GH2 each other and short the stocks with similar low GH2 each other due to independent sorting. This similarity enables comparison of return differences caused by changes in GH2 among GH1 groups by changing almost same amount of GH2 from the lowest GH2 portfolio to the highest GH2 portfolio in the GH1 group. If the returns of the self-financing portfolios formed on GH2 are different among the GH1 groups, in other words, the returns of the self-financing portfolios formed on GH2 change as the level of the GH1 changes, then it can be said that the effect of the change in GH2 on the returns of GH1 momentum portfolio depends on the level of GH1 and the main hypothesis of this study can be confirmed.

In addition to these portfolio approaches, I use Fama-MacBeth type regression. I use an interaction term between GH1 and GH2 to examine whether or not the interaction effect of the GH1 and the GH2 is significant which can support the hypothesis. I also include some variables known to predict stock returns to control for these variables. I run cross-sectional regression for the stock returns on the variables and test the significance of the averages of the coefficients on the variables across the cross-sectional regressions in the entire sample period. The regression model is as follows:

$$Return_{it} = \gamma_{0t} + \gamma_{1t}LnSize_{it-1} + \gamma_{2t}Ret6_{it-1} + \gamma_{3t}LnPrice_{it-1} + \gamma_{4t}IVOL_{it-1} + \gamma_{5t}Beta_{it-1} + \gamma_{6t}GH1_{it-1} + \gamma_{7t}GH2_{it-1} + \gamma_{8t}GH1GH2_{it-1} + \eta_{it},$$

where $Return_{it}$ is the average of six monthly returns of stock i from month $t + 1$ to month $t + 6$ of the stock i for the event month $t - 1$, $LnSize_{it-1}$ is the logarithm of the market capitalization of the stock i, which is the multiplication of the closing price and outstanding number of the shares at the end of the month $t - 1$ computed from CRSP files, $Ret6_{it-1}$ is the buy-and-hold return of the stock i over the past six months from month $t - 6$ to $t - 1$, $LnPrice_{it-1}$ is the logarithm of the closing price for the stock i at the end of the month $t - 1$, $IVOL_{it-1}$ is the standard deviation of the residuals from market model using daily returns data, multiplied by square root of the number of trading days during the 365 day period ending on the end of the month $t - 1$, $Beta_{it-1}$ is the stock's beta estimated from the market model used for IVOL calculation for the month $t - 1$, $GH1_{it-1}$ is the measure for the nearness of current price to 52-week high, $GH2_{it-1}$ is the measure for the remoteness of current price from 52-week low, and $GH1GH2_{it-1}$ is the interaction term of GH1 and GH2, which is the multiplication of GH1 and GH2 at the end of month $t - 1$.

My focus of the Fama-MacBeth type regression is the coefficient of the GH1 and GH2 interaction term. If the coefficient is significant, it means that the remoteness from 52-week low makes a difference among the stocks with different nearness to 52-week high.

CHAPTER THREE

RESULTS

3.1 Hypothesis 1

3.1.1 Univariate Results

Table 1 shows the average monthly returns over the six-month holding period for 10 portfolios based on GH1 and for 10 portfolios based on GH2.

It shows that there are strong momentum profits based on nearness of current price to 52-week high. The lowest GH1 portfolio makes a return of 0.45% per month, while the highest GH1 portfolio makes a return of 1.32% per month. The difference of 0.87% between these portfolio returns is statistically significant with a *t*-statistic of 8.22. The corresponding Fama French alpha[3] is 1.22% and statistically significant with a *t*-statistic of 14.6.

It also shows that the portfolio returns based on GH1 increase almost monotonically and consistently from the lowest GH1 portfolio to the highest GH1 portfolio. Therefore, these test results tell us that the nearer to 52-week high the stock price is, the higher the average monthly return across the six-month holding period is for the stock.

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[3] I follow Cooper et al. (2004) to compute Fama-French alpha.

Table 1

Average Monthly Returns of GH measure portfolios

Portfolio	GH1	GH2
Low	0.45	0.75
2	0.85	0.92
3	1.06	0.97
4	1.16	1.00
5	1.22	1.05
6	1.26	1.11
7	1.26	1.19
8	1.29	1.24
9	1.29	1.36
High	1.32	1.56
H - L	0.87	0.81
	(8.22)	(8.02)
Fama-French Alpha	1.22	0.81
	(14.6)	(10.73)

At the end of each month t - 1, all NYSE, AMEX and NASDAQ stocks are allocated into deciles based on their GH measures. GH1 is defined as the ratio of $P_{i,t-1}$ to $high_{i,t-1}$, where $P_{i,t-1}$ is the price of stock i at the end of month $t-1$ and $high_{i,t-1}$, is the highest price of stock i during the 365 day period that ends on the last day of the month $t-1$. GH2 is defined as the ratio of $P_{i,t-1}$ to $low_{i,t-1}$, where $P_{i,t-1}$ is the price of stock i at the end of month $t-1$ and $low_{i,t-1}$, is the lowest price of stock i during the 365 day period that ends on the last day of the month $t-1$. Stocks priced under \$5 or included in the lowest NYSE decile at the end of month $t-1$ are excluded. Returns of the portfolios are average returns across six monthly returns during holding period (months t+1 to t+6, skipping month t). Reported above are the mean monthly returns, return differences of extreme portfolios, and the corresponding alphas from Fama–French three factor model over the period 1966 to 2013. The returns are in percent and the t – statistics are reported in parentheses.

The table also shows that there are strong momentum profits based on remoteness of current price from 52-week low. The lowest GH2 portfolio makes a return of 0.75% per month, while the highest GH2 portfolio makes a return of 1.56% per month. The

difference of 0.81% between these portfolio returns is statistically significant with a *t*-statistic of 8.02. The corresponding Fama French alpha is 0.81% and statistically significant with a *t*-statistic of 10.73.

The table also shows that the portfolio returns based on GH2 increase almost monotonically and consistently from the lowest GH2 portfolio to the highest GH2 portfolio. Therefore, these test results tell us that the more remote from 52-week low the stock price is, the higher the average monthly return across the 6 month holding period is for the stock.

Jegadeesh and Titman (1993) show seasonality in momentum profits. Their test results show that the winners outperform the losers in all months except January, but the losers outperform the winners in January. Jegadeesh and Titman (2001) confirm this seasonality with the different sample period. Grundy and Martin (2001) also find the momentum profits differ between January and non-January months. Griffin et al. (2003) also show that the momentum profits are negative in January in their international data as in the U.S. data in other studies. George and Hwang (2004) also show that the momentum profits of the 52-week high strategy differ between January and non-January months.

To check if the momentum strategy with GH measures in our sample still show seasonality I discriminate January returns and returns of the months without January for our GH measure momentum strategy. Table 2 shows the average Jaunary and non-January returns over the six-month holding period for 10 portfolios based on GH1 and for 10 portfolios based on GH2. January returns are calculated when January falls in the six

holding months of the portfolios. Non-January returns are the average of the non-January month returns in portfolio holding period.

Table 2

Average Monthly Returns of GH measure portfolios for January and Non-January

	GH1		GH2	
Portfolio	January	Non-January	January	Non-January
Low	5.03	0.06	2.94	0.57
2	3.90	0.60	2.75	0.77
3	3.29	0.88	2.71	0.84
4	2.91	1.03	2.54	0.88
5	2.55	1.13	2.60	0.93
6	2.29	1.19	2.57	1.00
7	2.15	1.20	2.55	1.09
8	1.82	1.26	2.52	1.15
9	1.62	1.29	2.89	1.25
High	1.54	1.32	3.12	1.45
H - L	-3.49	1.26	0.18	0.88
	(-6.12)	(10.36)	(0.52)	(8.16)
Fama-French Alpha	-1.27	1.52	0.08	0.91
	(-3.14)	(15.28)	(0.26)	(11.93)

At the end of each month t - 1, all NYSE, AMEX and NASDAQ stocks are allocated into deciles based on their GH measures. GH1 is defined as the ratio of $P_{i,t-1}$ to $high_{i,t-1}$, where $P_{i,t-1}$ is the price of stock i at the end of month $t-1$ and $high_{i,t-1}$, is the highest price of stock i during the 365 day period that ends on the last day of the month $t-1$. GH2 is defined as the ratio of $P_{i,t-1}$ to $low_{i,t-1}$, where $P_{i,t-1}$ is the price of stock i at the end of month $t-1$ and $low_{i,t-1}$, is the lowest price of stock i during the 365 day period that ends on the last day of the month $t-1$. Stocks priced under $5 or included in the lowest NYSE decile at the end of month $t-1$ are excluded. January returns of the portfolios are the returns of January month if January is in the portfolio holding period (months t+1 to t+6, skipping month t). Non-January returns are average returns across five or six monthly returns during holding period (months t+1 to t+6, skipping month t). Reported above are the mean monthly returns, return differences of extreme portfolios, and the corresponding alphas from Fama–French three factor model over the period 1966 to 2013. The returns are in percent and the t – statistics are reported in parentheses.

Consistent with George and Hwang (2004), the January returns of the portfolios formed on GH1 decrease as the GH1 measure increases. The low GH1 measure portfolios show higher returns than the high GH1 measure portfolios in January. In contrast, non-January returns of the portfolios formed on GH1 increase as the GH1 measure increases. The high GH1 measure portfolios show higher returns than the low GH1 measure portfolios in non-January months. The January returns of the portfolios formed on GH2 do not decrease as the GH2 measure increases. The portfolio return of the highest GH2 measure is higher than that of the portfolio with the lowest GH2. However, the portfolio returns do not increase monotonically. Non-January returns of the portfolios formed on GH2 increase as the GH2 measure increases.

Therefore, the test results show that the seasonality in our momentum strategies with GH measures still exist but there are some diffrerences between the GH1 and GH2.

3.1.2 Dependent Sorts

Table 3 Panel A reports the average holding period returns of 25 equally weighted portfolios formed on the dependent double sorts based on GH1 and GH2. It also reports the return difference between the highest GH2 portfolio and the lowest GH2 portfolio within each GH1 group and the Fama-French alpha of the self-financing strategy that longs the highest GH2 portfolio and shorts the lowest GH2 portfolio within each GH1 group.

Table 3

Two-Way Dependent Sorts: Nearness to 52-week High Portfolio Returns and Then Remoteness from 52-week Low Portfolio Returns

	Panel A: Average Monthly Returns								
	GH2								
GH1	Low	2	3	4	High	H-L	*t*	FF α	*t*
Low	0.58	0.69	0.67	0.66	0.65	0.08	0.94	0.03	0.48
2	1.05	1.06	1.07	1.13	1.24	0.18	1.78	0.11	1.65
3	1.08	1.14	1.22	1.29	1.46	0.39	3.85	0.27	4.25
4	1.06	1.11	1.27	1.34	1.59	0.53	5.14	0.37	5.68
High	1.00	1.08	1.22	1.44	1.78	0.78	7.27	0.63	8.59

	Panel B: Average GH2					
	GH2					
GH1	Low	2	3	4	High	H-L
Low	1.05	1.14	1.24	1.40	2.06	1.01
2	1.09	1.19	1.30	1.48	2.19	1.10
3	1.12	1.23	1.35	1.54	2.27	1.15
4	1.17	1.29	1.41	1.61	2.35	1.18
High	1.23	1.38	1.53	1.76	2.67	1.44

All NYSE, AMEX and NASDAQ stocks are first sorted at the end of each month t -1 into quintiles based on their nearness to 52-week high (GH1). Each GH1 quintile is then further sorted into quintiles based on remoteness from 52-week low (GH2). Stocks priced under $5 or included in the lowest NYSE decile at the end of month $t - 1$ are excluded. Returns of the portfolios are average returns across six monthly returns during holding period (months $t + 1$ to $t + 6$, skipping month t). I report the mean monthly returns for these 25 portfolios over the period 1966 to 2013. The "H-L" column provides the mean returns of the strategy that buys the winner quintile and sells the loser quintile within each GH1 quintile (across each row). The Fama-French alphas corresponding to the mean returns of the long-short strategy are also shown. Panel B reports the average GH2 for each portfolio of the Panel A. The "H-L" column provides the GH2 differences between the highest GH2 and the lowest GH2 portfolio within each GH1 quintile.

Table 3 Panel A shows that the returns of GH2 quintiles within equivalent GH1 quintile increase almost monotonically and consistently from the lowest GH2 quintile to the highest GH2 quintile in all the GH1 quintiles. This means that the incremental role of the remoteness of current price from 52-week low (GH2) is positive within the equivalent 52-week high (GH1) momentum strategy. In other words, the more distant from the 52-week low the current price is, the higher the momentum profit is within the equivalent 52-week high group. Investors seem to be more reluctant to bid up the price when the price is far from 52-week low than when the price is near to 52-week low if the prices have equivalent nearness to the 52-week high. Investors might have more fear if the price is farther from 52-week low in this case even when the positive information still warrants more increase in stock price leading to momentum profits. Table 3 Panel B seems to explain these GH2 portfolio return increases within equivalent GH1 group by showing the average GH2 of the 25 portfolios. The average GH2 increases from the lowest GH2 portfolio to the highest GH2 portfolio in all GH1 quintiles.

Table 3 Panel B also shows that the differences in average GH2 within equivalent GH1 quintile across GH1 quintiles increase monotonically and consistently from the lowest GH1 group to the highest GH1 group. This implies that the return differences across GH1 quintiles between the lowest GH2 portfolio and the highest GH2 portfolio within each GH1 quintile in Panel A might result from the differences in GH2 measures rather than from different GH1 levels suggested by Hypothesis 1. Therefore, Table 3 Panel B confirms the necessity of independent sorts among GH1 and GH2 measures rather than dependent sorts for the test of Hypothesis 1.

3.1.3 Independent Sorts

Table 4 Panel A reports the average holding period returns of 25 equally weighted portfolios formed on the independent double sorts based on GH1 and GH2. It also reports the return differences between the highest GH2 portfolio and the lowest GH2 portfolio within each GH1 group and the Fama-French alpha of the self-financing strategy that longs the highest GH2 portfolio and shorts the lowest GH2 portfolio within each GH1 group.

Table 4

Two-Way Independent Sorts: Nearness to 52-week High Portfolio Returns and Then Remoteness from 52-week Low Portfolio Returns

	Panel A: Average Monthly Returns								
	GH2								
GH1	Low	2	3	4	High	H-L	*t*	FF α	*t*
Low	0.63	0.70	0.68	0.69	0.69	0.02	0.2	-0.01	-0.09
2	1.03	1.03	1.11	1.23	1.30	0.18	1.67	0.13	1.86
3	1.04	1.12	1.20	1.31	1.54	0.42	3.96	0.29	4.24
4	1.06	1.05	1.17	1.35	1.58	0.48	4.61	0.28	4.27
High	0.98	1.00	1.07	1.25	1.66	0.69	6.57	0.41	5.29

Table 4 (Continued)

	Panel B: Average GH2					
			GH2			
GH1	Low	2	3	4	High	H-L
Low	1.09	1.22	1.36	1.56	2.38	1.29
2	1.10	1.23	1.36	1.56	2.34	1.23
3	1.12	1.23	1.36	1.56	2.33	1.21
4	1.13	1.23	1.36	1.56	2.31	1.18
High	1.14	1.24	1.36	1.57	2.37	1.23

	Panel C: Average Number of Observations					
			GH2			
GH1	Low	2	3	4	High	Average
Low	141.73	72.37	53.58	44.80	40.17	70.53
2	99.43	80.57	63.59	55.85	53.84	70.65
3	63.61	81.27	75.34	68.44	64.60	70.65
4	34.62	71.34	83.94	84.55	78.45	70.58
High	15.62	46.78	76.81	99.64	115.81	70.93

All NYSE, AMEX and NASDAQ stocks are first sorted at the end of each month t -1 into quintiles based on their nearness to 52-week high (GH1). Each GH1 quintile is then further sorted into five groups based on remoteness from 52-week low (GH2). Stocks priced under $5 or included in the lowest NYSE decile at the end of month t – 1 are excluded. In Panel A, returns of the portfolios are average returns across six monthly returns during holding period (months t + 1 to t + 6, skipping month t). I report the mean monthly returns for these 25 portfolios over the period 1966 to 2013. The "H-L" column provides the mean returns of the strategy that buys the winner quintile and sells the loser quintile within each GH1 quintile (across each row). The Fama-French alphas corresponding to the mean returns of the long-short strategy are also shown. Panel B reports the average GH2 for each portfolio of the Panel A. The "H-L" column provides the GH2 differences between the highest GH2 and the lowest GH2 portfolio within each GH1 quintile. Panel C reports the average number of observations for each portfolio of the Panel A. The "Average" column provides the average number of observatons within each GH1 quintile.

In the highest GH1 quintile, the lowest GH2 portfolio makes a return of 0.98% per month while the highest GH2 portfolio makes a return of 1.66% per month. The difference of 0.69%[4] between these portfolio returns is statistically significant with a *t*-statistic of 6.57. The corresponding Fama French alpha is 0.41% and statistically significant with a *t*-statistic of 5.29. The other two higher GH1 quintiles show significant return differences of 0.48% and 0.42% between the lowest GH2 portfolio and the highest GH2 portfolio within each GH1 quintile. However, in the lower GH1 quintiles, the return difference between the lowest GH2 portfolio and the highest GH2 portfolio are 0.18%, 0.02%, respectively, and not statistically significant. The corresponding Fama French alpha is also not statistically significant with a *t*-statistic of 1.86 and -0.09. These results imply that the return differences across GH1 groups between the lowest GH2 portfolio and the highest GH2 portfolio are different depending on the level of the GH1 suggesting that Hypothesis 1 of this study cannot be rejected. It seems that investors are more sensitive to GH2 in higher GH1 group stocks, but, do not care a lot about GH2 in the lower GH1 group stocks.

Table 4 Panel A also shows that the portfolic return differences between the lowest GH2 and the highest GH2 portfolio increase almost monotonically and consistently from 0.02% of the lowest GH1 group to 0.69% of the highest GH1 group. This means that the impact of the remoteness of current price from 52-week low is more positive as the level of the nearness of current price to 52-week high increases in addition

[4] Since some months don't have either lowest or highest GH2 portfolio stocks due to independent sorts, return differences have some discrepancies with the differences in the entire average portfolio returns.

to the results that the impact is different depending on the level of the nearness of current price to 52-week high above.

Therefore, these test results confirm the Hypothesis 1 that the effect in the momentum returns produced by the change in the remoteness of current price from 52-week low depends on the level of the nearness of current price to 52-week high and also confirm that the effect increases in the positive direction as expected.

Table 4 Panel B reports the average GH2 of 25 portfolios. It shows that GH1 groups have almost similar GH2 for each GH2 portfolio each other as expected in independent sorts. Therefore, this table tells us that the return differences across GH1 groups come from almost same change in GH2 as intended in this test.

Table 4 Panel C reports the average number of observations of the 25 portfolios. As expected in these independent sort tests, there are some differences in average number of observations among the portfolios, but, overall, the numbers are not too small to lead to practical concerns.

3.1.4 Fama-MacBeth Regression

Table 5 shows the results of Fama-MacBeth type regression regarding the GH measures. The regression results show that the coefficient of the interaction term of GH1 and GH2 is positive (1.32) and statistically significant (t-statistics, 6.28) controlling for other variables.

This implies that the interaction effect between the nearness of the price to 52-week high and the remoteness of the price from 52-week low is statistically significant. The effect in the holding period returns of stock produced by changing the remoteness of

its price from 52-week low depends on the the nearness of its price to 52-week high level, vice versa. Therefore, these results confirm Hypothesis 1.

The table also shows that the coefficients of GH1 and GH2 are positive (1.41, 0.22, respectively) and significant (*t*-statistics, 8.7, 4.52, respectively) in the regression without the interaction term, which is consistent with the results in the univariate tests.

Table 6 shows the results of Fama-MacBeth type regression regarding the GH measures for January and non-January. The coefficient of the interaction term of GH1 and GH2 for January is still positive (3.50) and significant (*t*-statistics, 4.53) in January meaning the effectiveness of interaction between the GH1 and GH2 in January. The table also shows that, in the regression without the interaction term, the coefficients of GH1 and GH2 are negative (-2.44, -1.05) and significant (*t*-statistics, -3.3, -5.06). Therefore, though GH1 and GH2 have negative effect in returns in January, it seems that the interaction between GH1 and GH2 still exists in January. In non-January months, the GH1 and GH2 interaction term shows positive and significant coefficients and GH1 and GH2 coefficients without the interaction term also show positive and significant coefficients.

Table 5

Fama-MacBeth Cross-Sectional Regression

	γ	
	(1)	(2)
Intercept	0.11 (0.49)	1.46 (4.64)
Lnsize	-0.09 (-6.02)	-0.08 (-5.84)
Ret6	0.38 (4.36)	0.30 (3.39)
Lnprice	-0.09 (-3.4)	-0.09 (-3.36)
IVOL	-0.76 (-4.36)	-0.67 (-3.79)
Beta	0.02 (0.28)	0.01 (0.18)
GH1	1.41 (8.7)	-0.19 (-0.63)
GH2	0.22 (4.52)	-0.87 (-4.74)
GH1GH2		1.32 (6.28)

In each month t from 1966 to 2013, cross-sectional regression of the following form is estimated for stocks listed on NYSE, AMEX and NASDAQ: $\text{Return}_{it} = \gamma_{0t} + \gamma_{1t}\text{LnSize}_{it-1} + \gamma_{2t}\text{Ret6}_{it-1} + \gamma_{3t}\text{LnPrice}_{it-1} + \gamma_{4t}\text{IVOL}_{it-1} + \gamma_{5t}\text{Beta}_{it-1} + \gamma_{6t}\text{GH1}_{it-1} + \gamma_{7t}\text{GH2}_{it-1} + \gamma_{8t}\text{GH1GH2}_{it-1} + \eta_{it}$, where Return_{it} is the average of six monthly returns from month $t + 1$ to month $t + 6$ of the stock i in the event month t, LnSize_{it-1} is the logarithm of the market capitalization of the stock i, which is the multiplication of the closing price and outstanding number of the shares at the end of the month $t - 1$ computed from CRSP files, Ret6_{it-1} is the buy-and-hold return of the stock i over the past six months from month $t - 6$ to $t - 1$, LnPrice_{it-1} is the logarithm of the closing price for the stock i at the end of the month $t - 1$, IVOL_{it-1} is the standard deviation of the residuals from market model using daily returns data, multiplied by square root of the number of trading days during the 365 day period ending on the end of the month t - 1, Beta_{it-1} is the stock's beta estimated from the market model used for IVOL calculation for the month $t - 1$, GH1_{it-1} is the measure for the neaness of current price to 52-week high, GH2_{it-1} is the measure for the remoteness of current price from 52-week low, and GH1GH2_{it-1} is the interaction term of GH1 and GH2, which is the multiplication of GH1 and GH2 at the end of month $t - 1$. I exclude stocks with price less than $5 or with market capitalization below the NYSE smallest decile market capitalization cutoff at the end of the month t - 1. The t -statistics are reported in parentheses.

Table 6

Fama-MacBeth Cross-Sectional Regression (Seasonality)

	January		Non_January	
	(1)	(2)	(3)	(4)
Intercept	7.34	10.69	-0.55	0.63
	(7.47)	(8.01)	(-2.41)	(1.99)
Lnsize	-0.18	-0.17	-0.08	-0.07
	(-3.79)	(-3.64)	(-5.18)	(-5.03)
Ret6	1.49	1.28	0.26	0.19
	(4.77)	(4.17)	(2.85)	(2.05)
Lnprice	-1.31	-1.31	0.02	0.03
	(-11.39)	(-11.41)	(0.91)	(0.94)
IVOL	3.85	4.10	-1.12	-1.04
	(6.6)	(6.9)	(-6.2)	(-5.7)
Beta	0.47	0.46	-0.01	-0.02
	(2.11)	(2.09)	(-0.22)	(-0.33)
GH1	-2.44	-6.58	1.78	0.39
	(-3.3)	(-5.1)	(10.84)	(1.28)
GH2	-1.05	-3.85	0.33	-0.61
	(-5.06)	(-5.18)	(6.62)	(-3.32)
GH1GH2		3.50		1.14
		(4.53)		(5.33)

In each month t from 1966 to 2013, cross-sectional regression of the following form is estimated for stocks listed on NYSE, AMEX and NASDAQ: $Return_{it} = \gamma_{0t} + \gamma_{1t}LnSize_{it-1} + \gamma_{2t}Ret6_{it-1} + \gamma_{3t}LnPrice_{it-1} + \gamma_{4t}IVOL_{it-1} + \gamma_{5t}Beta_{it-1} + \gamma_{6t}GH1_{it-1} + \gamma_{7t}GH2_{it-1} + \gamma_{8t}GH1GH2_{it-1} + \eta_{it}$, where $Return_{it}$ is the January return or the average of non-January returns from month $t + 1$ to month $t + 6$ of the stock i in the event month t, $LnSize_{it-1}$ is the logarithm of the market capitalization of the stock i, which is the multiplication of the closing price and outstanding number of the shares at the end of the month $t - 1$ computed from CRSP files, $Ret6_{it-1}$ is the buy-and-hold return of the stock i over the past six months from month $t - 6$ to $t - 1$, $LnPrice_{it-1}$ is the logarithm of the closing price for the stock i at the end of the month $t - 1$, $IVOL_{it-1}$ is the standard deviation of the residuals from market model using daily returns data, multiplied by square root of number of trading days in the month t - 1, $Beta_{it-1}$ is the stock's beta estimated from the market model used for IVOL calculation in the month $t - 1$, $GH1_{it-1}$ is the measure for the neaness of current price to 52-week high, $GH2_{it-1}$ is the measure for the remoteness of current price from 52-week low, and $GH1GH2_{it-1}$ is the interaction term of GH1 and GH2, which is the multiplication of GH1 and GH2 at the end of month $t - 1$. I exclude stocks with price less than \$5 or with market capitalization below the NYSE smallest decile market capitalization cutoff at the end of the month t - 1. The t -statistics are reported in parentheses.

3.2 Hypothesis 2

3.2.1 Use of Three Size Groups

The second hypothesis hypothesizes that momentum profit of the strategy considering both the nearness to 52-week high and the remoteness from 52-week low is more prominent in small size stocks than that in large size stocks.

To test this hypothesis, I group the stocks in the sample into three terciles based on their size. If the profits of the self-financing strategy using both the 52-week high and 52-week low is larger for the small size group than for the large size group, then it can be said that the small stocks explain large portion of momentum profits even in the strategy of 52-week high in consideration of 52-week low and the second hypothesis will be confirmed.

Using the size of the stock at the end of the portfolio formation month, I make three samples, small, medium, and large stock group, from the entire stock sample used in the test of Hypothesis 1. And then I apply the investment strategy within each group.

Table 7 shows the average number of stocks and the size of stock in each size group. The time-series averages of the number of stocks in each size group at the portfolio formation month are 588, 589, and 588, respectively. The numbers are similar because I group the stocks into terciles. The time-series averages of the average size of stocks at the portfolio formation month in each size group are $176.0 million, $550.2 million, and $6,811.7 million, respectively during the entire period 1966 to 2012. The average sizes show quite a difference between small stock group and large stock group.

Table 7

Average Number of Stocks and Size of Stock in Each Size Group

	Number	Min	Mean	Max
Small	588	21.6	176.0	675.1
Medium	589	79.0	550.2	1,988.4
Large	588	993.3	6,811.7	21,572.4

All NYSE, AMEX and NASDAQ stocks are sorted at the end of each month t -1 into terciles based on their size. Stocks priced under $5 or included in the lowest NYSE decile at the end of month t – 1 are excluded. The "Number" is the time-series average of number of stocks in each size group. The "Min" is the minimum during the entire period of the average size of stock in each size group at the end of each month t -1. The "Mean" is the time-series average of the average size of stock in each size group at the end of each month t -1. The "Max" is the maximum during the entire period of the average size of stock in each size group at the end of each month t -1. Size figures are in million dollars.

3.2.2 Univariate Results

Table 8 shows the average monthly returns over the six-month holding period for the portfolios based on GH1 and GH2 in each size group. All the size groups show that there are momentum profits for the portfolios based on GH measures. The table also shows that the portfolio returns based on these measures increase overall monotonically and consistently from the lowest GH measure portfolio to the highest GH measure portfolio in each size group. One exception is the returns of portfolios based on GH1 in large group.

The return differences between the highest GH1 portfolio and the lowest GH1 portfolio in each size group show that the momentum profits of the self-financing strategy on GH1 are the largest in the small stock group among those three size groups. The return difference of the long-short strategy for the small stock portfolios is 1.14%

and that for the medium and large size stock portfolio is 0.90% and 0.56% respectively. The return differences between highest GH2 portfolio and the lowest GH2 portfolio in each size group also show that the momentum profits of the self-financing strategy on GH2 are the largest in the small stock group among those three size groups. The return difference of the long-short strategy for the small stock portfolios is 0.87% and that for the medium and large size stock portfolio is 0.74% and 0.62% respectively.

Therefore, from these comparisons it can be inferred that the momentum profits based on GH measures arise largely from small stocks. These results are consistent with other studies such as Hong et al. (2000) and Jegadeesh and Titman (2001).

3.2.3 Size Effect on the Strategy on both GH1 and GH2

Table 9 reports the average holding period returns of 25 equally weighted portfolios formed on the dependent double sorts based on GH1 and GH2 in each size group.

Table 8

Average Monthly Returns of GH measure portfolios of Each Size Group

	Small		Mid		Large	
Portfolio	GH1	GH2	GH1	GH2	GH1	GH2
Low	0.35	0.69	0.51	0.81	0.53	0.77
2	0.73	0.92	0.85	0.96	0.90	0.88
3	1.03	1.02	1.09	1.01	1.01	0.91
4	1.23	1.04	1.17	1.05	1.04	0.95
5	1.25	1.13	1.27	1.12	1.08	0.92
6	1.39	1.26	1.29	1.13	1.07	0.94
7	1.42	1.29	1.33	1.22	1.10	1.04
8	1.45	1.38	1.35	1.28	1.12	1.04
9	1.52	1.54	1.30	1.41	1.06	1.13
High	1.49	1.56	1.40	1.55	1.09	1.39
H - L	1.14	0.87	0.90	0.74	0.56	0.62
	(9.73)	(8.36)	(7.94)	(6.85)	(5.73)	(5.74)
Fama-French Alpha	1.45	0.83	1.20	0.78	0.82	0.71
	(15.4)	(10.16)	(12.48)	(9.54)	(9.9)	(8.28)

All NYSE, AMEX and NASDAQ stocks are sorted at the end of each month t -1 into terciles based on their size. In each size group the stocks are allocated into deciles based on their GH measures. GH1 is defined as the ratio of $P_{i,t-1}$ to $high_{i,t-1}$, where $P_{i,t-1}$ is the price of stock i at the end of month $t-1$ and $high_{i,t-1}$, is the highest price of stock i during the 365 day period that ends on the last day of the month $t-1$. GH2 is defined as the ratio of $P_{i,t-1}$ to $low_{i,t-1}$, where $P_{i,t-1}$ is the price of stock i at the end of month $t-1$ and $low_{i,t-1}$, is the lowest price of stock i during the 365 day period that ends on the last day of the month $t-1$. Stocks priced under \$5 or included in the lowest NYSE decile at the end of month $t-1$ are excluded. Returns of the portfolios are average returns across six monthly returns during holding period (months t+1 to t+6, skipping month t). Reported above are the mean monthly returns, return differences of extreme portfolios, and the corresponding alphas from Fama–French three factor model over the period 1966 to 2013. The returns are in percent and the t – statistics are reported in parentheses.

Table 9

Average Monthly Returns of Each Size Group: Two-Way Dependent Sorts

Panel A: Average Monthly Returns of Small Size Stocks									
	GH2								
GH1	Low	2	3	4	High	H-L	*t*	FF α	*t*
Low	0.51	0.54	0.57	0.57	0.50	0.00	0.04	-0.08	-0.98
2	1.13	1.00	1.07	1.18	1.26	0.13	1.14	0.07	0.87
3	1.09	1.28	1.31	1.42	1.48	0.39	3.13	0.22	2.55
4	1.16	1.26	1.46	1.58	1.72	0.56	4.71	0.33	4.05
High	1.16	1.25	1.54	1.72	1.85	0.69	5.44	0.44	4.71
Extreme						1.39	11.59	1.53	12.99

Panel B: Average Monthly Returns of Medium Size Stocks									
	GH2								
GH1	Low	2	3	4	High	H-L	*t*	FF α	*t*
Low	0.56	0.72	0.72	0.63	0.75	0.19	1.76	0.20	2.24
2	1.16	1.10	1.08	1.12	1.20	0.03	0.32	0.02	0.24
3	1.16	1.21	1.27	1.32	1.45	0.28	2.56	0.22	2.94
4	1.11	1.20	1.35	1.45	1.59	0.48	4.44	0.34	4.49
High	1.03	1.15	1.29	1.52	1.80	0.77	6.76	0.66	7.88
Extreme						1.27	10.51	1.50	13.16

Table 9 (Continued)

Panel C: Average Monthly Returns of Large Size Stocks									
	GH2								
GH1	Low	2	3	4	High	H-L	*t*	FF α	*t*
Low	0.73	0.75	0.73	0.72	0.66	-0.05	-0.54	-0.07	-0.83
2	0.98	1.00	1.01	0.98	1.16	0.18	1.84	0.16	2.06
3	0.98	1.05	1.03	1.11	1.22	0.23	2.39	0.23	3.07
4	0.98	0.99	1.02	1.11	1.44	0.46	4.53	0.45	5.74
High	0.86	0.90	1.01	1.13	1.49	0.63	5.84	0.62	7.29
Extreme						0.81	6.87	1.07	9.7

All NYSE, AMEX and NASDAQ stocks are sorted at the end of each month t -1 into terciles based on their size. In each size group the stocks are first sorted at the end of each month t -1 into quintiles based on their nearness to 52-week high (GH1). Each GH1 quintile is then further sorted into quintiles based on remoteness from 52-week low (GH2). Stocks priced under $5 or included in the lowest NYSE decile at the end of month $t - 1$ are excluded. Returns of the portfolios are average returns across six monthly returns during holding period (month $t + 1$ to $t + 6$, skipping month t). I report the mean monthly returns for these 25 portfolios over the period 1966 to 2013 of each size group. Panel A, B, and C report the returns for small, medium, and large size group, respectively. The "H-L" column provides the mean returns of the strategy that buys the winner quintile and sells the loser quintile within each GH1 quintile (across each row). The extreme portfolio longs the highest GH1 and highest GH2 stocks and shorts the lowest GH1 and lowest GH2 stocks. The "H-L" column provides the mean returns of this strategy. The Fama-French alphas corresponding to the mean returns of the long-short strategy are also shown.

With regard to the extreme portfolio that longs the portfolio with the highest GH1 and the highest GH2 and shorts the portfolio with the lowest GH1 and the lowest GH2, the return differences for small, medium, and large size group are 1.39%, 1.27%, and 0.81%, respectively. These return differences are statistically significant with *t*-statistics of 11.59, 10.51, and 6.87, respectively. The corresponding Fama and French alphas for small, medium, and large size group are 1.53%, 1.50%, and 1.07%, respectivley and statistically significant with *t*-statistics of 12.99, 13.16, and 9.7, respectively.

Therefore, from these comparisons it can be inferred that the momentum profits based on both GH1 and GH2 also arise largely from small stocks and the Hypothesis 2 can be confirmed.

3.2.4 Size Effect on the Strategy on both GH1 and GH2 – Seasonality

Table 10 reports the January and non-January average holding period returns of self-financing strategies in each size group using 25 equally weighted portfolios based on GH1 and GH2 dependent double sorts.

The test results show that the momentum profits in January of the strategy using both 52-week high and 52-week low are negative for all the size group and are explained by Fama-French Model. However, the momentum profits in non-January months of the strategy using both 52-week high and 52-week low are positive for all the size group and those of the small size group are the largest of all the size groups. The profits are also not explained by Fama-French Model. Considering these test results it can be said that the the momentum profits of the extreme portfolios based on both GH1 and GH2 shown in entire sample arise largely from small stock returns in non-January.

Table 10

Average Monthly Return Differences of Each Size Group: Two-Way Dependent Sorts in January and Non-January Months

Panel A: Small Size Stocks								
	GH2							
	January				Non-January			
GH1	H-L	*t*	FF α	*t*	H-L	*t*	FF α	*t*
Low	0.08	0.22	-0.40	-1.12	-0.01	-0.13	-0.05	-0.54
2	0.74	1.91	0.49	1.43	0.09	0.79	0.07	0.78
3	1.47	3.75	0.61	1.96	0.32	2.41	0.21	2.34
4	1.27	3.46	0.16	0.61	0.53	4.23	0.37	4.41
High	1.80	4.57	0.45	1.53	0.63	4.75	0.46	4.75
Extreme	-1.63	-3.09	-0.62	-1.3	1.68	12.93	1.80	13.95

Panel B: Medium Size Stocks								
	GH2							
	January				Non-January			
GH1	H-L	*t*	FF α	*t*	H-L	*t*	FF α	*t*
Low	0.62	1.69	0.55	1.62	0.16	1.36	0.19	2
2	0.20	0.53	0.16	0.5	0.04	0.34	0.02	0.28
3	0.33	0.96	-0.27	-1.04	0.30	2.52	0.27	3.4
4	0.61	1.74	0.18	0.73	0.49	4.23	0.40	4.81
High	0.78	2.19	0.55	1.81	0.79	6.67	0.72	8.26
Extreme	-1.42	-2.56	-0.40	-0.76	1.51	11.76	1.73	13.75

Table 10 (Continued)

Panel C: Large Size Stocks								
	GH2							
	January				Non-January			
GH1	H-L	*t*	FF α	*t*	H-L	*t*	FF α	*t*
Low	-0.39	-1.05	-0.71	-2.08	-0.03	-0.29	-0.03	-0.33
2	0.33	0.93	-0.02	-0.07	0.17	1.63	0.17	2.11
3	0.49	1.31	0.39	1.26	0.23	2.09	0.23	3.05
4	0.47	1.24	0.67	2.18	0.47	4.3	0.46	5.8
High	0.68	1.85	0.73	2.42	0.65	5.52	0.65	7.41
Extreme	-1.30	-2.72	-0.30	-0.65	1.02	8.3	1.24	11.02

All NYSE, AMEX and NASDAQ stocks are sorted at the end of each month t -1 into terciles based on their size. In each size group the stocks are first sorted at the end of each month t -1 into quintiles based on their nearness to 52-week high (GH1). Each GH1 quintile is then further sorted into quintiles based on remoteness from 52-week low (GH2). Stocks priced under $5 or included in the lowest NYSE decile at the end of month t – 1 are excluded. January returns of the portfolios are the returns of January month if January is in the portfolio holding period (month t+1 to t+6, skipping month t). Non-January returns are average returns across five or six monthly returns during holding period (month t+1 to t+6, skipping month t). I report the mean monthly returns of the strategy that buys the winner GH2 quintile and sells the loser GH2 quintile within each GH1 quintile for these 25 portfolios over the period 1966 to 2013 of each size group. Panel A, B, and C report the returns for small, medium, and large size group, respectively. The "H-L" column provides the mean returns of the strategy that buys the winner GH2 quintile and sells the loser GH2 quintile within each GH1 quintile. The extreme portfolio longs the highest GH1 and highest GH2

3.3 Robustness

To test the robustness of the Hypothesis 1, I tested with the data that includes the stocks less than $5 and the stocks that would fall in the smallest NYSE size decile at the end of portfolio formation month. The test procedures are the same as those for Hypothesis 1.

The test results show that there are still monmentum profits for the GH measure portfolios. Both GH1 and GH2 make momentum profits monotonically and consistently from the lowest to the highest GH portfolio[5]. However, the return differences between the lowest and highest GH measure portfolios are smaller in the data of this robustness test which has no restriction on price and size than in restricted data in Hypothesis 1 test. This means that momentum profits based on GH measures are also low if low price stocks and small stocks are included as known on the other momentum strategies. Seasonality test results seem to give some explanations for this low return differences in no restriction data. The low GH measure portfolios in no restriction data show quite a big returns in January compared to the low GH measure portfolios in restriction data in January – the lowest GH1 portfolio shows 14.19% and the lowest GH2 portfolio shows 7.02% in January in no restriction data while the lowest GH1 and GH2 portfolio in restricted data has 5.03% and 2.94%, respectively.

I also find that the incremental role of GH2 for the momentum strategy based on GH1 is still statistically significant in the no restriction data. Furthermore, as in the restriction data test, the impact of GH2 on momentum profits is different depending on the level of GH1 and gives more momentum profits as the levels of GH1 increase confirming Hypothesis 1 (Table 11) . Different from the univariate tests, double sorts test results show that the momentum profits increase 0.07% to 0.74% along the different levels of GH1 at the similar rate to that in the data with restriction which shows increase from 0.02% to 0.69% in Table 4. The Fama-MacBeth regression test results also confirm the interaction effect between GH1 and GH2.

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[5] Test results are shown in the tables in the Appendix.

Table 11

Two-Way Independent Sorts: Nearness to 52-week High Portfolio Returns and Then Remoteness from 52-week Low Portfolio Returns (No Restriction)

	Panel A: Average Monthly Returns								
	GH2								
GH1	Low	2	3	4	High	H-L	*t*	FF α	*t*
Low	1.10	1.11	1.12	1.08	1.17	0.07	0.72	0.11	1.25
2	1.03	1.12	1.21	1.35	1.46	0.43	3.93	0.31	4.25
3	1.12	1.20	1.30	1.49	1.69	0.57	5.31	0.37	5.82
4	1.11	1.15	1.32	1.48	1.80	0.69	6.5	0.43	6.86
High	1.12	1.10	1.21	1.40	1.82	0.74	7.35	0.41	5.9

	Panel B: Average GH2					
	GH2					
GH1	Low	2	3	4	High	H-L
Low	1.07	1.21	1.36	1.58	2.47	1.40
2	1.09	1.21	1.36	1.58	2.47	1.38
3	1.10	1.22	1.36	1.58	2.46	1.36
4	1.11	1.22	1.36	1.58	2.43	1.32
High	1.12	1.22	1.36	1.58	2.47	1.36

Table 11 (Continued)

	Panel C: Average Number of Observations					
	GH2					
GH1	Low	2	3	4	High	Average
Low	239.81	127.36	97.74	83.72	80.89	125.90
2	174.39	139.27	114.02	102.65	99.78	126.02
3	122.55	142.94	127.89	119.09	117.64	126.02
4	68.63	131.76	147.97	146.26	135.32	125.99
High	26.88	86.87	142.46	178.39	196.08	126.14

All NYSE, AMEX and NASDAQ stocks are first sorted at the end of each month t -1 into quintiles based on their nearness to 52-week high (GH1). Each GH1 quintile is then further sorted into five groups based on remoteness from 52-week low (GH2). Stocks priced under $5 or included in the lowest NYSE decile at the end of month $t - 1$ are included. In Panel A, returns of the portfolios are average returns across six monthly returns during holding period (month $t + 1$ to $t + 6$, skipping month t). I report the mean monthly returns for these 25 portfolios over the period 1966 to 2013. The "H-L" column provides the mean returns of the strategy that buys the winner quintile and sells the loser quintile within each GH1 quintile (across each row). The Fama-French alphas corresponding to the mean returns of the long-short strategy are also shown. Panel B reports the average GH2 for each portfolio of the Panel A. The "H-L" column provides the GH2 differences between the highest GH2 and the lowest GH2 portfolio within each GH1 quintile. Panel C reports the average number of observations for each portfolio of the Panel A. The "Average" column provides the average number of observatons within each GH1 quintile.

CHAPTER FOUR

CONCLUSION

Prior study shows the usefulness of the nearness to 52-week high as a reference point for momentum strategy. It is shown that as the price of a stock gets close to its 52-week high the holding period return of the stock become larger than the stock of which the current price is not close to its 52-week high.

However, dispite the same readiness for availability of 52-week low as 52-week high, the role of the remoteness of current price from the 52-week low has not been clear.

The reason why the stocks close to 52-week high have momentum returns is claimed to be that even though new good information pushes the stock close to its 52-week high irrational investors are reluctant to bid for the stocks near 52-week high because the investors feel the stock price has risen too high to buy even if the information warrants it. When the information eventually prevails the price moves up, resulting in a continuation and momentum profits for rational investors.

If the fear of the irrational investors affects the momentum of the stock near 52-week high then it is possible that 52-week low affects the momentum because the remoteness of current price from 52-week low enables the investors to determine whether the current stock price has risen a lot from the 52-week low when the current price is close to 52-week high.

Therefore, it seems presumable that even among the stocks with equivalent nearness to 52-week high the stock far from 52-week low would give more fear to investors than the stock close to 52-week low because the investor would feel the former has risen a lot from its lowest price while they feel the latter has not risen much considering the lowest price (52-week low). This could result in more momentum returns for the stock more remote from 52-week low than for the stock less remote from 52-week low despite their equivalent nearness to 52-week high.

Furthermore, if I group stocks into several groups based on their nearness to 52-week high from the lowest nearness to the highest nearness, there seems to be some differences in the investors' reluctance to bid the stocks between these groups. For the stocks in the high nearness to 52-week high group, investors might be more sensitive to the stock's 52-week low than for the stocks in the low nearness to 52-week high group. Investors could feel fear about the stocks in the high nearness to 52-week high group and be sensitive to the 52-week low and this high sensitivity to the remoteness from 52-week low could lead to great momentum return differences between the low remoteness from 52-week low and the high remoteness from 52-week low stocks within that equivalent nearness to 52-week high group. However, they might not feel fear and not care a lot about the stocks in the low nearness to 52-week high group and not be so sensitive to the 52-week low. This possibility could result in differences in the role of 52-week low between the groups categorized by 52-week high. In other words, there could be an intereaction effect between the nearness of current price to 52-week high and the remoteness of current price from 52-week low. In this study this possibility is examined.

I use 25 equally weighted portfolios double sorted on the nearness to 52-week high and the remoteness from 52-week low to find whether the remoteness from 52-week low makes a difference in momentum returns among different nearness to 52-week high stock groups.

The test of dependent double-sorts results show that within the equivalent GH1 group the return of the portfolio based on GH2 increases as the GH2 increases meaning the incremental role of the remoteness from 52-week low to the momentum strategy based on the nearness to 52-week high. In the highest GH1 group, the GH2 portfolio returns increase from 1.00% to 1.78% per month and the second highest GH1 group, GH2 portfolio returns increase from 1.06% to 1.59% per month. The rest of the GH1 groups also show increases in GH2 portfolio returns.

The test results of independent double-sorts show that the average return differences between the stocks far from 52-week low and the stocks close to 52-week low increase from 0.02% per month for the lowest GH1 group to 0.18%, 0.42%, 0.48%, and 0.69% per month for the highest GH1 group as the level of the nearness to 52-week high increases. This means that the role of the remoteness of current price from 52-week low to the momentum strategy on nearness of current price to 52-week high depends on the level of the nearness of current price to 52-week high and the direction of the change is positive confirming Hypothesis 1.

I also use Fama-MacBeth type regression to find whether or not the interaction effect between the nearness to 52-week high and the remoteness from 52-week low exists. The results of the regression tests show that the coefficient of the interaction term

between the nearness to 52-week high and the remoteness from 52-week low is statistically significant. It means that the effect in the holding period returns of stock produced by changing the remoteness of its price from 52-week low depends on the the nearness of its price to 52-week high level, vice versa. Therefore, these results confirm the existence of the interaction effect between the nearness to 52-week high and the remoteness from 52-week low confirming Hypothesis 1 that says that the effect in the momentum returns produced by the change in the remoteness of current price from 52-week low depends on the level of the nearness of current price to 52-week high. These test results suggest that investor investment decision could depend not only on 52-week high price but also on 52-week low price and the use of one varies depending on the level of the other.

It is known by studies that the momentum profits occur largely from small stocks. In other words, the large portion of the momentum profits of self-financing strategy using past winners and losers can be said to come from small stocks in the portfolio.

Under the Hypothesis 1 of this study, I build self-financing portfolio using both 52-week high and 52-week low on double sorting method and examine the size effect on this strategy. The self-financing portfolio longs the stocks with both the highest nearness to 52-week high and the highest remoteness from 52-week low and shorts the stocks with both the lowest nearness to 52-week high and the lowest remoteness from 52-week low.

I find that the large portion of momentum profits of the strategy come from small size stocks. The small stock self-financing strategy produces 1.39% monthly return on

average and the large stock self-financing strategy produces 0.81% monthly return on average.

I check the robustness of the hypothesis by not excluding the stocks priced less than $5 and the stocks that would fall in the smallest decile of NYSE that are included in the main hypothesis test. The test results show that the remoteness of current price from 52-week low makes differences in the momentum strategies depending on the level of 52-week high confirming the robustness of Hypothesis 1.

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APPENDIX

TABLES ON ROBUSTNESS TESTS

Table A1

Average Monthly Returns of GH measure portfolios (No Restriction)

Portfolio	GH1	GH2
Low	1.10	1.01
2	1.10	1.03
3	1.16	1.10
4	1.25	1.12
5	1.33	1.19
6	1.38	1.28
7	1.39	1.36
8	1.42	1.45
9	1.41	1.64
High	1.45	1.78
H - L	0.34	0.77
	(2.14)	(8.49)
Fama-French Alpha	0.59	0.71
	(4.75)	(10.13)

At the end of each month t - 1, all NYSE, AMEX and NASDAQ stocks are allocated into deciles based on their GH measures. GH1 is defined as the ratio of *Pi,t-1* to *highi,t-1*, where *Pi,t-1* is the price of stock i at the end of month t – 1 and *highi,t-1*, is the highest price of stock i during the 365 day period that ends on the last day of the month t – 1. GH2 is defined as the ratio of *Pi,t-1* to *lowi,t-1*, where *Pi,t-1* is the price of stock i at the end of month t – 1 and *lowi,t-1*, is the lowest price of stock i during the 365 day period that ends on the last day of the month t – 1. Stocks priced under $5 or included in the lowest NYSE decile at the end of month t – 1 are included. Returns of the portfolios are average returns across six monthly returns during holding period (month t+1 to t+6, skipping month t). Reported below are the mean monthly returns, return differences of extreme portfolios, and the corresponding alphas from Fama–French three factor model over the period 1966 to 2013. The returns are in percent and the t – statistics are reported in parentheses.

Table A2

Average Monthly Returns of GH measure portfolios for January and Non-January (No Restriction)

	GH1		GH2	
Portfolio	January	Non-January	January	Non-January
Low	14.19	-0.08	7.02	0.46
2	8.87	0.42	5.29	0.66
3	6.69	0.69	5.01	0.76
4	5.31	0.91	4.77	0.80
5	4.47	1.07	4.69	0.89
6	3.70	1.19	4.87	0.98
7	3.23	1.25	4.83	1.07
8	2.75	1.31	4.94	1.16
9	2.35	1.34	5.46	1.32
High	2.20	1.40	6.26	1.41
H - L	-11.99	1.49	-0.76	0.94
	(-12.99)	(8.98)	(-2.05)	(9.99)
Fama-French Alpha	-8.79	1.50	-0.80	0.90
	(-13.55)	(11.27)	(-2.33)	(12.84)

At the end of each month t - 1, all NYSE, AMEX and NASDAQ stocks are allocated into deciles based on their GH measures. GH1 is defined as the ratio of *Pi,t-1* to *highi,t-1*, where *Pi,t-1* is the price of stock i at the end of month t – 1 and *highi,t-1*, is the highest price of stock i during the 365 day period that ends on the last day of the month t – 1. GH2 is defined as the ratio of *Pi,t-1* to *lowi,t-1*, where *Pi,t-1* is the price of stock i at the end of month t – 1 and *lowi,t-1*, is the lowest price of stock i during the 365 day period that ends on the last day of the month t – 1. Stocks priced under $5 or included in the lowest NYSE decile at the end of month t – 1 are included. January returns of the portfolios are the returns of January month if January is in the portfolio holding period (month t+1 to t+6, skipping month t). Non-January returns are average returns across five or six monthly returns during holding period (month t+1 to t+6, skipping month t). Reported below are the mean monthly returns, return differences of extreme portfolios, and the corresponding alphas from Fama–French three factor model over the period 1966 to 2013. The returns are in percent and the t – statistics are reported in parentheses.

Table A3

Two-Way Dependent Sorts: Nearness to 52-week High Portfolio Returns and Then Remoteness from 52-week Low Portfolio Returns (No Restriction)

Panel A: Average Monthly Returns									
	GH2								
GH1	Low	2	3	4	High	H-L	*t*	FF α	*t*
Low	1.17	1.06	1.05	1.12	1.10	-0.11	-1.12	-0.06	-0.79
2	1.00	1.09	1.19	1.29	1.45	0.44	4.18	0.31	4.37
3	1.11	1.22	1.28	1.46	1.69	0.58	5.59	0.38	6.14
4	1.11	1.19	1.40	1.51	1.82	0.71	6.98	0.49	7.93
High	1.10	1.17	1.35	1.57	1.94	0.84	7.8	0.61	8.72

Panel B: Average GH2						
	GH2					
GH1	Low	2	3	4	High	H-L
Low	1.03	1.12	1.24	1.42	2.18	1.14
2	1.07	1.18	1.30	1.50	2.33	1.26
3	1.10	1.22	1.34	1.56	2.41	1.31
4	1.15	1.27	1.40	1.61	2.46	1.31
High	1.21	1.36	1.52	1.77	2.76	1.55

All NYSE, AMEX and NASDAQ stocks are first sorted at the end of each month t -1 into quintiles based on their nearness to 52-week high (GH1). Each GH1 quintile is then further sorted into quintiles based on remoteness from 52-week low (GH2). Stocks priced under $5 or included in the lowest NYSE decile at the end of month $t - 1$ are included. Returns of the portfolios are average returns across six monthly returns during holding period (month $t + 1$ to $t + 6$, skipping month t). I report the mean monthly returns for these 25 portfolios over the period 1966 to 2013. The "H-L" column provides the mean returns of the strategy that buys the winner quintile and sells the loser quintile within each GH1 quintile (across each row). The Fama-French alphas corresponding to the mean returns of the long-short strategy are also shown. Panel B reports the average GH2 for each portfolio of the Panel A. The "H-L" column provides the GH2 differences between the highest GH2 and the lowest GH2 portfolio within each GH1 quintile.

Table A4

Fama-MacBeth Cross-Sectional Regression (No Restriction)

	γ	
	(1)	(2)
Intercept	0.15 (0.75)	1.75 (6.21)
Lnsize	-0.04 (-3.14)	-0.04 (-2.86)
Ret6	0.42 (6.00)	0.32 (4.58)
Lnprice	-0.35 (-10.89)	-0.34 (-10.69)
IVOL	0.30 (2.17)	0.42 (2.99)
Beta	-0.06 (-1.26)	-0.07 (-1.47)
GH1	1.93 (12.12)	-0.06 (-0.22)
GH2	0.02 (0.49)	-1.27 (-8.83)
GH1GH2		1.60 (8.99)

In each month from 1966 to 2013, cross-sectional regression of the following form is estimated for stocks listed on NYSE, AMEX and NASDAQ: $Return_{it} = \gamma_{0t} + \gamma_{1t}LnSize_{it-1} + \gamma_{2t}Ret6_{it-1} + \gamma_{3t}LnPrice_{it-1} + \gamma_{4t}IVOL_{it-1} + \gamma_{5t}Beta_{it-1} + \gamma_{6t}GH1_{it-1} + \gamma_{7t}GH2_{it-1} + \gamma_{8t}GH1GH2_{it-1} + \eta_{it}$, where $Return_{it}$ is the average of six monthly returns from month $t + 1$ to month $t + 6$ of the stock i in the event month t -1, $LnSize_{it-1}$ is the logarithm of the market capitalization of the stock i, which is the multiplication of the closing price and outstanding number of the shares at the end of the month $t - 1$ computed from CRSP files, $Ret6_{it-1}$ is the buy-and-hold return of the stock i over the past six months from month $t - 6$ to $t - 1$, $LnPrice_{it-1}$ is the logarithm of the closing price for the stock i at the end of the month $t - 1$, $IVOL_{it-1}$ is the standard deviation of the residuals from market model using daily returns data, multiplied by square root of the number of trading days during the 365 day period ending on the end of the month t - 1, $Beta_{it-1}$ is the stock's beta estimated from the market model used for IVOL calculation for the month $t - 1$, $GH1_{it-1}$ is the measure for the nearness of current price to 52-week high, $GH2_{it-1}$ is the measure for the remoteness of current price from 52-week low, and $GH1GH2_{it-1}$ is the interaction term of GH1 and GH2, which is the multiplication of GH1 and GH2 at the end of month $t - 1$. I include stocks with price less than $5 or with market capitalization below the NYSE smallest decile market capitalization cutoff at the end of the month t - 1. The t -statistics are reported in parentheses.

Table A5

Fama-MacBeth Cross-Sectional Regression: Seasonality (No Restriction)

	January		Non_January	
	(1)	(2)	(3)	(4)
Intercept	12.89	17.27	-1.00	0.33
	(13.77)	(13.66)	(-4.92)	(1.17)
Lnsize	-0.13	-0.12	-0.03	-0.03
	(-3.02)	(-2.81)	(-2.33)	(-2.09)
Ret6	-0.16	-0.49	0.47	0.40
	(-0.60)	(-1.83)	(6.73)	(5.59)
Lnprice	-2.22	-2.17	-0.19	-0.18
	(-16.38)	(-16.32)	(-5.85)	(-5.72)
IVOL	6.83	7.23	-0.29	-0.20
	(17.30)	(17.90)	(-2.10)	(-1.43)
Beta	-0.20	-0.22	-0.05	-0.06
	(-1.00)	(-1.15)	(-0.97)	(-1.13)
GH1	-5.09	-10.70	2.57	0.94
	(-6.51)	(-8.53)	(15.95)	(3.33)
GH2	-0.49	-4.13	0.07	-0.98
	(-3.33)	(-7.41)	(1.74)	(-6.99)
GH1GH2		4.61		1.30
		(7.18)		(7.48)

In each month from 1966 to 2013, cross-sectional regression of the following form is estimated for stocks listed on NYSE, AMEX and NASDAQ: $Return_{it} = \gamma_{0t} + \gamma_{1t}LnSize_{it-1} + \gamma_{2t}Ret6_{it-1} + \gamma_{3t}LnPrice_{it-1} + \gamma_{4t}IVOL_{it-1} + \gamma_{5t}Beta_{it-1} + \gamma_{6t}GH1_{it-1} + \gamma_{7t}GH2_{it-1} + \gamma_{8t}GH1GH2_{it-1} + \eta_{it}$, where $Return_{it}$ is the January return or the average of non-January returns from month $t + 1$ to month $t + 6$ of the stock i in the event month $t - 1$, $LnSize_{it-1}$ is the logarithm of the market capitalization of the stock i, which is the multiplication of the closing price and outstanding number of the shares at the end of the month $t - 1$ computed from CRSP files, $Ret6_{it-1}$ is the buy-and-hold return of the stock i over the past six months from month $t - 6$ to $t - 1$, $LnPrice_{it-1}$ is the logarithm of the closing price for the stock i at the end of the month $t - 1$, $IVOL_{it-1}$ is the standard deviation of the residuals from market model using daily returns data, multiplied by square root of the number of trading days during the 365 day period ending on the end of the month $t - 1$, $Beta_{it-1}$ is the stock's beta estimated from the market model used for IVOL calculation for the month $t - 1$, $GH1_{it-1}$ is the measure for the neaness of current price to 52-week high, $GH2_{it-1}$ is the measure for the remoteness of current price from 52-week low, and $GH1GH2_{it-1}$ is the interaction term of GH1 and GH2, which is the multiplication of GH1 and GH2 at the end of month $t - 1$. I include stocks with price less than \$5 or with market capitalization below the NYSE smallest decile market capitalization cutoff at the end of the month $t - 1$. The t-statistics are reported in parentheses.