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Industry information and the 52-week high effect☆

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ABSTRACT

We find that the 52-week high effect (George and Hwang, 2004) cannot be explained by standard risk factors. Instead, it is more consistent with investor underreaction caused by anchoring bias: the presumably more sophisticated institutional investors suffer less from this bias and buy (sell) stocks close to (far from) their 52-week highs. Further, the effect is mainly driven by investor underreaction to industry instead of firm-specific information. The extent of underreaction is more for positive than for negative industry information. The 52-week high strategy works best among stocks with high factor model R-squares and high industry betas (i.e., stocks whose values are more affected by industry factors and less affected by firm-specific information). An industry 52-week high strategy to buy (sell) industries whose total capitalizations are close to (far from) their 52-week highs outperforms an idiosyncratic 52-week high strategy to buy stocks with prices close to their 52-week highs and short stocks in the same industry with prices far from their 52-week highs.

1. Introduction

The “52-week high effect” was first documented by George and Hwang (2004), who find that stocks with prices close to their 52-week highs have better subsequent returns than stocks with prices far from their 52-

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week highs. George and Hwang (2004) argue that investors use the 52-week high as an "anchor" against which they value stocks. When stock prices are near the 52-week highs, investors are unwilling to bid the price all the way to the fundamental value. As a result, investors underreact when stock prices approach their 52-week highs, and this creates the 52-week high effect. Li and Yu (2012) find that there is also a 52-week high effect on the market index: the nearness to the Dow 52-week high positively predicts future aggregate market returns.

In this paper, we show that the 52-week high effect is mainly driven by investor underreaction to industry instead of firm-specific information. Specifically, we design an idiosyncratic 52-week high strategy and an industry 52-week high strategy based on the original 52-week high trading strategy proposed by George and Hwang (2004), which we call the individual 52-week high strategy. The idiosyncratic 52-week high trading strategy involves buying stocks whose prices are close to their 52-week highs and shorting the same dollar amount of stocks in the same industry whose prices are far away from their 52-week highs. This strategy is thus industry-neutral, and the profit associated with it is mainly driven by firm-specific information. In contrast, the industry 52-week high strategy involves buying industries whose total market capitalizations are close to their 52-week highs and shorting industries whose total market capitalizations are far from their 52-week highs. Because we buy and short whole industries in this strategy, the profit associated with it is mainly driven by industry information. We find that the industry 52-week high strategy is more profitable than the idiosyncratic 52-week high strategy, suggesting that the 52-week high effect may be mainly driven by investor underreaction to industry instead of firm-specific information. We also find that the industry 52-week high strategy is slightly more profitable than the individual 52-week high trading strategy proposed by George and Hwang (2004). Using all stocks listed on NYSE, AMEX, and NASDAQ from 1963 to 2009, the industry 52-week high strategy generates a monthly return of 0.46%, higher than the 0.32% from the idiosyncratic 52-week high strategy, and is also slightly higher than the 0.43% from the individual 52-week high strategy in the same period.

While anchoring bias could be the reason behind the 52-week high effect, an alternative explanation is that stocks with prices close to 52-week highs are riskier than other stocks. In fact, the recent literature has made some progress on the rational explanation for profits from the momentum strategy by linking it to macroeconomic variables (e.g., Liu and Zhang, 2008; Li, 2012; Li and Zhang, 2013; Liu and Zhang, 2013). If firms are ex ante identical but ex post different with firm-specific shocks, and they have time-varying betas to some risk factors, we can potentially observe a 52-week high effect.[1]

If the 52-week high effect is indeed caused by anchoring bias, then we would expect more sophisticated investors to suffer less from this bias and buy (sell) stocks whose prices are close to (far from) the 52-week highs. In contrast, less sophisticated investors should suffer more from this bias and trade in the opposite direction. On the other hand, if the 52-week high effect is driven by risk factors, then the trading strategy is no longer profitable after we properly control for different risks. Further, sophisticated investors should not buy (sell) stocks whose prices are close to (far from) the 52-week highs because the higher return is simply the compensation for higher risks associated with the trading strategy, and there is no risk-adjusted abnormal return.

Many previous studies find that institutional investors are more sophisticated than individual investors (Gompers and Metrick, 2001; Cohen et al., 2002; Sias et al., 2006; Amihud and Li, 2006). Therefore, we use institutional investors to proxy for sophisticated investors. We find that institutional investors buy (sell) stocks whose prices are close to (far from) the 52-week highs. We control for standard risk factors and find that the 52-week high effect still exists. Thus, the evidence seems to be consistent with the underreaction explanation rather than the risk-based explanation.[2]

We then go one step further in trying to understand what type of information investors underreact to. Is it true that investors underreact mainly to industry instead of firm-specific information? Do investors underreact to positive or negative information? How can one design a better investment strategy based

[1] For example, Li (2012) proposes a rational risk-based model in which firms have time-varying exposures to the price of investment goods and neutral productivity shocks. The model can simultaneously explain momentum profits and the value premium.

[2] However, it is possible that the 52-week high effect is driven by risk factors that we have not controlled for. We thank an anonymous referee for pointing this out.

on the answers to these questions? What are the implications of these findings for the efficient market hypothesis?

We find further evidence that the 52-week high effect is mainly driven by investor underreaction to industry instead of firm-specific information. The individual 52-week high strategy used by George and Hwang (2004) works best among stocks with high factor model R-squares and high industry betas (i.e., stocks whose values are more affected by industry factors and less affected by firm-specific information) and does not work among stocks with low factor model R-squares and low industry betas. We also find that investor underreaction to positive news accounts more for the profits associated with the 52-week high strategy than investor underreaction to negative news. Given that it is positive news that pushes stock prices to their 52-week highs, the finding is not surprising. The Daniel et al. (1997; DGTW hereafter) benchmark-adjusted return for stocks in industries in which market values are close to 52-week highs is 0.24% per month, much larger than the 0.07% per month from shorting stocks in industries in which market values are far from 52-week highs. These returns imply that the industry 52-week high strategy is not highly affected by costs associated with short-selling: the buy-only portfolio accounts for most of the profits. Our finding also casts doubt on market efficiency. Given that the trading strategy is based on publicly available information and does not require extensive short-selling, why do prices not adjust to the information and eliminate the trading profits?

George and Hwang (2004) point out that the 52-week high price is a piece of highly observable information and readily available in the financial media. Therefore, investors use it as a reference point in valuing stocks. Similarly, Li and Yu (2012) find that the most visible Dow index has more predictive power than the economically more meaningful market capitalization from NYSE/Amex. Our results that the 52-week high effect is mainly driven by industry information instead of firm-specific information is consistent with the evidence in the literature that investors respond more to industry information and respond less (or even ignore) firm-specific information. For example, Cooper et al. (2001) find that investors increased their valuation of firms by 74% around announcements that firms added “dot com” to their names in the late 1990s, even though many of these firms' core businesses were not Internet-related. Peng and Xiong (2006) show that because attention is a scarce cognitive resource, investors tend to process more sector information and less firm-specific information. When investors are severely attention constrained, they pay no attention to firm-specific information.

Our results may also offer insights on how to design better investment strategies based on 52-week highs. First, our results indicate that the individual 52-week high strategy proposed by George and Hwang (2004) is more profitable for stocks with high industry betas and high factor model R-squares. Second, investors can earn higher profits if they buy (short) all stocks in industries in which the total market capitalizations are close to (far from) 52-week highs instead of trading on individual stocks based on the 52-week high effect.

To provide further evidence that our industry 52-week high strategy is consistent with investor underreaction to public information due to anchoring bias, we divide industries into different groups based on how informative, on average, the stock price of firms in the industry is. We would expect investors to suffer more anchoring bias when the industry information is hard to value and when the stock price is less informative in the industry. We use five measures of price informativeness widely recognized in the literature: firm size, firm age, price impact, analyst coverage, and institutional ownership. Our industry 52-week high effect is more pronounced among industries whose stock prices are hard to value, namely, industries with small firms, young firms, firms with large price impacts, firms with low analyst coverage, and firms with relatively low institutional ownership.

Following the prior literature (e.g., George and Hwang, 2004; Jegadeesh and Titman, 1993; Moskowitz and Grinblatt, 1999), we form equal-weighted portfolios when designing our industry 52-week high strategy. One criticism is that since we hold our portfolios for six months, we need to rebalance our portfolios at the end of each month in order to keep them equal-weighted. The rebalancing can be potentially costly if the transaction cost is high. We address this issue by considering two variations in our strategy. First, we consider a modified industry 52-week high strategy in which we form an equal-weighted portfolio at the end of each month t, but do not rebalance in the next six months; i.e., we calculate the buy-and-hold return of the portfolio. Second, since we have shown that the industry 52-week high strategy is more profitable among small firms, investors can always implement the industry 52-week high strategy using only small stocks and form value-weighted portfolios, which do not require rebalancing, either. We find that the industry 52-week high strategy is still highly profitable using either of the above two modifications, so portfolio rebalancing is not necessary.

The rest of the paper is structured as follows. In Section 2, we discuss related literature. In Section 3, we describe data and sample selection and report some baseline results. Section 4 presents results on what drives the 52-week high effect. Section 5 reports some robustness tests, and Section 6 concludes.

2. Related literature

Several recent studies have documented that the 52-week high has predictive ability for stock returns. George and Hwang (2004) find that the average monthly return for the 52-week high strategy is 0.45% from 1963 to 2001, and the return does not reverse in the long run. Li and Yu (2012) examine the 52-week high effect on the aggregate market return. They use the nearness to the 52-week high and the nearness to the historical high as proxies for the degree of good news that traders have underreacted and overreacted to in the past. For the aggregate market returns, they find their nearness to the 52-week high measure positively predicts future market returns, while the nearness to the historical high negatively predicts future returns. They also find that the predictive power from these proxies is stronger than traditional macro variables. Liu et al. (2011) find that the 52-week high effect also exists in the international stock markets.

The 52-week high can not only predict future stock returns, it also affects mergers and acquisitions, the exercise of options, mutual fund returns and flows, stock betas, return volatility, and trading volume. Baker et al. (2009) examine the 52-week high effect on mergers and acquisitions. They find that mergers and acquisitions offer prices are biased toward the 52-week high, a largely irrelevant past price, and the modal offer price is exactly that reference price. They also find that an offer's probability of acceptance discontinuously increases when the offer exceeds that 52-week high; conversely, bidder shareholders react increasingly negatively as the offer price is pulled upward toward that price.

The 52-week high price is not only a reference point for mergers and acquisitions, but also a reference point for the exercise of options. Heath et al. (1999) investigate stock option exercise decisions by more than 50,000 employees at seven corporations. They find that employee exercise activity roughly doubles when the stock price exceeds the maximum price attained during the previous year. They interpret this behavior as evidence that individual option-holders set a reference point based on the maximum stock price that was achieved within the previous year, and option-holders are more likely to exercise when subsequent price movements move past that reference point.

Sapp (2011) documents a 52-week high effect for mutual fund returns and cash flows. He examines the performance of trading strategies for mutual funds based on an analogous one-year high measure for the net asset value of fund shares, prior extreme returns, and fund sensitivity to stock return momentum. He finds all three measures have significant, independent predictive power for fund returns, whether measured in raw or risk-adjusted returns. He also finds that nearness to the one-year high is a significant predictor of fund monthly cash flows.

Driessen et al. (2010) examine stock betas, return volatilities, and option-implied volatility changes when stock prices approach their 52-week highs and also when stock prices break through those highs. They find that betas and volatilities decrease when stock prices approach 52-week highs, and volatilities increase after breakthroughs. The effects are economically large and significant and consistent across stock and stock option markets.

Huddart et al. (2008) examine the volume and price patterns around 52-week highs and lows. Based on a random sample of 2000 firms drawn from the CRSP in the period from November 1, 1982, to December 31, 2006, they find that volume is strikingly higher, in both economic and statistical terms, when the stock price crosses either the 52-week high or low. And this increase in volume is more pronounced the longer the time since the stock price last achieved the price extreme, the smaller the firm, and the higher the individual investor interest in the stock.

Tversky and Kahneman (1974) discuss the concept of *anchoring*, which describes the common human tendency to rely too heavily on one piece of information when making decisions. George and Hwang (2004) argue that investors use the 52-week high as an anchor when they evaluate new information. Burghof and Prothmann (2009) test George and Hwang's (2004) anchoring bias hypothesis. Motivated by a result from the literature that behavioral biases increase under uncertainty (Daniel et al., 1998 and Daniel et al., 2001; Hirshleifer, 2001), they examine whether the 52-week high price has more predictive power in cases of larger information uncertainty.

Using firm size (market value), book-to-market ratio, nearness to the 52-week high price, stock price volatility, firm age, and cash flow volatility as proxies for information uncertainty, they find that 52-week high strategy profits are increasing in uncertainty measures, which means that the anchoring bias hypothesis cannot be rejected.

3. Data, methods, and baseline results

To test whether the profits from the 52-week high strategy documented in George and Hwang (2004) are mainly driven by industry or firm-specific information, we design an industry 52-week high strategy and an idiosyncratic 52-week high strategy. For convenience, we call the 52-week high strategy in George and Hwang (2004) the individual 52-week high strategy. We first define $PRILAG_{i,t}$ as

$$PRILAG_{i,t} = \frac{Price_{i,t}}{52weekhigh_{i,t}} \tag{1}$$

where $Price_{i,t}$ is stock i's price at the end of month t, and $52weekhigh_{i,t}$ is the highest price for stock i during the 12-month period that ends on the last day of month t.[3] Price information is obtained from CRSP. The individual 52-week high strategy involves buying stocks in the winner portfolio and shorting stocks in the losing portfolio at the end of each month t, where the winner (loser) portfolio consists of the 30% of stocks with the highest (lowest) value of $PRILAG_{i,t}$. We hold the portfolio for six months. To construct the idiosyncratic 52-week high strategy, we first use two-digit SIC codes to form 20 industries following Moskowitz and Grinblatt (1999).[4] In each month t, we define the winner (loser) portfolio as the 30% of stocks with the highest (lowest) value of $PRILAG_{i,t}$ in each industry. In the idiosyncratic 52-week high strategy, we buy stocks in the winner portfolio and short stocks in the loser portfolio and hold them for six months. Since we buy and short equal dollar amont of stocks in each industry, the industry information in these stocks will more or less cancel out. Therefore, the profit produced by the idiosyncratic 52-week high strategy is mainly driven by firm-specific information instead of industry information.

To construct the industry 52-week high strategy, we first define $MKTVLAG_{j,t}$ as

$$MKTVLAG_{j,t} = \frac{MktValue_{j,t}}{52weekhigh_{j,t}} \tag{2}$$

where $MktValue_{j,t}$ is industry j's market value at the end of month t, measured as the sum of the market values of all stocks in industry j. $52weekhigh_{j,t}$ is the highest value of $MktValue_{j,t}$ during the 12-month period that ends on the last day of month t.[5] The industry 52-week high strategy involves buying stocks in the six industries with the highest value of $MKTVLAG_{j,t}$ and shorting stocks in the six industries with the lowest value of $MKTVLAG_{j,t}$. Since we buy and short the entire industries, the idiosyncratic information in these portfolios is more or less diversified away. Therefore, the profit produced by the industry 52-week high strategy is mainly driven by industry instead of firm-specific information.

For all the above three strategies, we hold the portfolios for six months. The return on the winner (loser) portfolio in month $t + k$ is the equal-weighted return of all stocks in the portfolio, where $k = 1, \ldots, 6$. Stock returns are obtained from CRSP, and we use the corrections suggested in Shumway (1997).[6] We compute the average monthly returns from July 1963 to December 2009. Results are reported in Table 1.

Panel A in Table 1 shows that the individual 52-week high strategy generates an average monthly return of 0.43% in our sample period, close to the 0.45% documented in George and Hwang (2004) from July 1963 to

[3] Consistent with George and Hwang (2004), we find that a strategy based on 52-week lows is not profitable. George and Hwang (2004) conjecture that this is possibly due to the tax distortion associated with the strategy (page 2170).

[4] See Table I in Moskowitz and Grinblatt (1999) for a description of the 20 industries.

[5] In an earlier version of this paper, we define $MktValue_{j,t}$ as the value weighted average of individual stock's $PRILAG_{i,t}$ in the industry and we find qualitatively similar results. We choose this measure because intuitively, the market value of an industry is a better heuristic for investors to anchor their beliefs. For example, Fidelity Investments provides the market capitalization of different industries to their investors.

[6] Specifically, if a stock is delisted for performance reasons and the delist return is missing in CRSP, we set the delist return to −0.30 for NYSE/AMEX stocks and −0.55 for NASDAQ stocks. We obtain very similar results when we use only CRSP delist returns without filling missing performance-related delist returns.

Table 1
Profits from individual, idiosyncratic, and industry 52-week high strategies.

	Raw return			DGTW return		
	Winner	Loser	Winner–Loser	Winner	Loser	Winner–Loser
Panel A: all months included						
Individual	1.35%	0.92%	0.43%	0.11%	0.03%	0.08%
	(6.41)	(2.88)	(1.74)	(3.53)	(0.50)	(0.94)
Industry	1.39%	0.93%	0.46%	0.24%	−0.07%	0.31%
	(5.00)	(3.13)	(3.67)	(5.30)	(−1.35)	(3.74)
Idiosyncratic	1.31%	0.99%	0.32%	0.10%	0.05%	0.04%
	(5.91)	(2.63)	(1.60)	(4.02)	(1.20)	(0.67)
Industry − Idio			0.14%			0.27%
			(0.67)			(2.35)
Idio − Individual			−0.11%			−0.04%
			(−1.68)			(−0.95)
Industry − Individual			0.03%			0.23%
			(0.11)			(2.00)
Panel B: excluding January						
Individual	1.21%	0.05%	1.16%	0.16%	−0.10%	0.26%
	(5.63)	(0.12)	(4.51)	(5.17)	(−1.75)	(3.08)
Industry	1.02%	0.44%	0.58%	0.22%	−0.11%	0.33%
	(3.66)	(1.48)	(4.14)	(5.05)	(−1.98)	(3.86)
Idiosyncratic	1.16%	0.17%	0.98%	0.14%	−0.06%	0.20%
	(5.13)	(0.47)	(5.00)	(6.06)	(−1.40)	(3.35)
Industry − Idio			−0.40%			0.13%
			(−2.05)			(1.20)
Idio − Individual			−0.17%			−0.06%
			(−2.30)			(−1.41)
Industry − Individual			−0.58%			0.08%
			(−2.49)			(0.69)
Panel C: January only						
Individual	2.95%	10.57%	−7.62%	−0.45%	1.45%	−1.90%
	(4.09)	(6.42)	(−5.63)	(−3.84)	(4.71)	(−4.84)
Industry	5.57%	6.44%	−0.87%	0.43%	0.35%	0.08%
	(6.23)	(5.54)	(−1.90)	(3.08)	(2.60)	(0.39)
Idiosyncratic	3.04%	10.08%	−7.04%	−0.42%	1.29%	−1.70%
	(4.12)	(6.54)	(−5.98)	(−3.70)	(4.83)	(−4.84)
Industry − Idio			6.17%			1.78%
			(6.67)			(3.95)
Idio − Individual			0.58%			0.20%
			(2.63)			(1.97)
Industry − Individual			6.75%			1.98%
			(6.26)			(4.13)

This table reports the average monthly portfolio returns from July 1963 through December 2009 for individual, idiosyncratic, and industry 52-week high strategies. All portfolios are held for 6 months. The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks in CRSP; t-statistics in parentheses are based on Newey–West standard errors with three lags.

December 2001. The industry 52-week high strategy generates a monthly return of 0.46%, and the profit is statistically different from zero at any conventional level ($t = 3.67$). In contrast, the idiosyncratic 52-week high strategy generates a monthly return of 0.32%, and the profit is not statistically different from zero.

The returns to the three 52-week high strategies may be driven by certain firm characteristics. In particular, firms with prices close to their 52-week highs most likely have experienced high returns in the past several months, and the profits could be due to the return momentum effect. To test whether this is the case, we use the DGTW benchmark-adjusted returns instead of raw returns. Specifically, we group stocks into 125 portfolios (quintiles based on size, book-to-market, and return momentum) and calculate the DGTW benchmark-adjusted return for a stock as its raw return minus the value-weighted average return of the portfolio to which it belongs.

The last three columns in Panel A of Table 1 show that size, book-to-market ratio, and return momentum can indeed explain part of the profits generated by the three strategies. The average monthly profit of the individual 52-week high strategy is reduced to 0.08% and is not statistically different from zero. In contrast, we still have a sizeable 0.31% average monthly abnormal return associated with the industry 52-week high strategy, which remains highly significant statistically and economically. The average monthly profit of the idiosyncratic 52-week high strategy is 0.04% and not statistically different from zero. Further, the differences between the profits associated with the industry 52-week high strategy and the other two strategies are statistically significant: it outperforms the idiosyncratic 52-week high strategy by 0.27% per month and the individual 52-week high strategy by 0.23% per month. Therefore, the results seem to indicate that the 52-week high effect is mainly driven by industry instead of firm-specific information.

Most of the profits from the industry 52-week high strategy come from the buy portfolio. Buying stocks in the six industries with the highest $MKTVLAG_{j,t}$ produces an average monthly DGTW benchmark-adjusted return of 0.24%. In contrast, the profit from shorting stocks in the six industries with the lowest $MKTVLAG_{j,t}$ is only 0.07%. Therefore, close to 80% of the DGTW-adjusted profits from the industry 52-week high strategy is generated by the buy portfolio. As a result, the industry 52-week high strategy is highly implementable because most of the profits do not require shorting, which can be costly to implement.

George and Hwang (2004) document that the return to the individual 52-week high strategy is actually negative in January because loser stocks tend to rebound in January. Jegadeesh and Titman (1993) also document a negative return to the individual momentum strategy in January for the same reason. To examine whether the industry 52-week high strategy loses money in January, we exclude returns in January and repeat our analyses. Panel B of Table 1 shows that after excluding January, the profits to the individual 52-week high strategy and the idiosyncratic 52-week high strategy increase dramatically, whereas the profits to the industry 52-week high strategy increase only slightly, especially for the DGTW benchmark-adjusted return. The results imply that the returns to the individual 52-week high strategy and the idiosyncratic 52-week high strategy are highly negative in January, whereas the profit to the industry 52-week high strategy is near zero in January. The pattern is clearly borne out in Panel C, where we report the returns in January only. The profit to the individual 52-week high strategy is −7.62% (−1.90% based on DGTW benchmark-adjusted return), and the profit to the idiosyncratic 52-week high strategy is −7.04% (−1.70% based on DGTW benchmark-adjusted return) in January. The profit to the industry 52-week high strategy is −0.87% in January, and it becomes positive (though not significantly different from zero) based on DGTW benchmark-adjusted return.

The above results regarding profits to the three strategies in January and excluding January are consistent with previous results in the literature. The value premium is very strong in January, and there is a negative correlation between momentum profits and the value premium (e.g., Li, 2012). Further, the value premium is mainly an intra-industry effect (e.g., Cohen and Polk, 1999). Because both individual and idiosyncratic 52-week high strategies contain a large intra-industry component, excluding January will have a large impact. In contrast, the industry 52-week high strategy uses mainly inter-industry information, and excluding January will have a much smaller impact.[7]

To summarize, we find that the industry 52-week high strategy is significantly more profitable than the individual 52-week high strategy or the idiosyncratic 52-week high strategy, both economically and statistically. Further, the profit of the industry 52-week high strategy stems mainly from the buy portfolio.

4. What drives the 52-week high effect?

4.1. Institutional demand and the 52-week high strategy

To further test whether the 52-week high effect is driven by anchoring bias or risk factors, we examine the relation between institutional demand and the 52-week high effect. By definition, shares not held by

[7] We thank an anonymous referee for pointing this out.

institutional investors (more sophisticated) are held by individual investors (less sophisticated). While the anchoring bias hypothesis predicts that institutional investors buy (sell) stocks whose prices are close to (far from) 52-week highs, the risk factor hypothesis predicts no difference in institutional demand between the two groups of stocks. Further, since we have shown in Table 1 that the industry 52-week high strategy is more profitable than the individual 52-week high strategy, the anchoring bias hypothesis predicts that institutional investors buy (sell) industries whose market capitalizations are close to (far away from) their 52-week highs.

We use two measures of institutional demand from Thomson Financial's CDA/Spectrum 13F filings: the change in the fraction of shares held by institutional investors and the change in the number of institutions holding the stock. Because 13F filings report institutional holdings at the end of each calendar quarter, we look at institutional demand change from quarter to quarter. In Panel A of Table 2, we rank stocks based on their closeness to the 52-week high (i.e., based on the value of $PRILAG_{i,t}$) at the end of quarter t and examine the average value of institutional demand changes for firms in each group in the next four quarters.

Panel A of Table 2 shows that, from quarter t to $t+1$, institutional investors increase their holdings of stocks whose prices are close to 52-week highs by 0.47% of shares outstanding. In contrast, they decrease their holdings of stocks whose prices are far from 52-week highs by 0.33%. The difference between the winner and loser groups is 0.80% and highly statistically significant ($t = 9.45$). In the second subsequent quarter (from quarter $t+1$ to $t+2$), we find a similar pattern, though the magnitude is smaller, with a 0.55% difference between the winner and loser groups. The magnitude becomes even smaller in the third and fourth quarters, but there are still significant differences in institutional demand change between the winner and loser groups.

The change in the number of institutions holding the firm's stocks shows a similar pattern. In quarter $t+1$, the number of institutional investors increases by 2.06 for stocks whose prices are close to 52-week highs. In contrast, the number decreases by 0.61 for stocks whose prices are far from 52-week highs. The difference

Table 2
Institutional demand in individual and industry 52-week high portfolios.

	Change in institutional holding				Change in investor number			
	Loser	Middle	Winner	W–L	Loser	Middle	Winner	W–L
Panel A: institutional demand in individual 52-week high portfolios								
t + 1	−0.33%	0.45%	0.47%	0.80%	−0.61	0.81	2.06	2.67
	(−3.16)	(5.50)	(7.41)	(9.45)	(−3.77)	(4.97)	(9.52)	(10.52)
t + 2	−0.17%	0.31%	0.39%	0.55%	−0.18	0.81	1.57	1.75
	(−1.71)	(3.78)	(5.74)	(7.60)	(−1.22)	(5.15)	(8.27)	(10.19)
t + 3	−0.06%	0.24%	0.30%	0.35%	0.01	0.77	1.35	1.34
	(−0.60)	(2.94)	(3.89)	(4.59)	(0.06)	(4.87)	(7.72)	(9.62)
t + 4	0.02%	0.21%	0.19%	0.17%	0.15	0.75	1.19	1.04
	(0.22)	(2.61)	(2.50)	(2.26)	(1.07)	(4.75)	(6.59)	(8.24)
Panel B: institutional demand in industry 52-week high portfolios								
t + 1	0.55%	1.46%	2.13%	1.58%	2.93	6.94	8.64	5.71
	(0.80)	(1.82)	(3.11)	(4.15)	(2.00)	(3.72)	(5.63)	(6.11)
t + 2	0.93%	1.43%	1.19%	0.26%	4.92	7.64	5.62	0.70
	(1.28)	(1.73)	(2.02)	(0.72)	(3.63)	(4.09)	(3.65)	(0.69)
t + 3	0.92%	1.45%	0.76%	−0.16%	4.17	7.92	5.74	1.57
	(1.31)	(1.68)	(1.40)	(−0.44)	(2.93)	(4.13)	(3.82)	(1.48)
t + 4	0.91%	1.13%	0.70%	−0.20%	4.16	7.47	5.80	1.64
	(1.29)	(1.46)	(1.00)	(−0.49)	(2.77)	(4.01)	(3.65)	(1.36)

This table reports quarterly changes in total institutional holding and changes in the number of total institutional investors holding the stocks in individual (Panel A) and industry (Panel B) 52-week high portfolios. Total institutional holding of a stock in a quarter is defined as the number of shares held by all institutional investors at the end of that quarter divided by the number of shares outstanding. The individual 52-week high winner (loser) portfolio is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) industries in the industry 52-week high strategy are the top (bottom) 30% industries with the highest (lowest) ratio of current industry market cap to the 52-week high value of the industry cap. For each portfolio, we report the change in institutional holding and the change in the number of institutions holding the stock for quarters $t+1$ to $t+4$. t-statistics in parentheses are based on Newey–West standard errors with three lags.

between the winner and loser groups is highly statistically significant. In the next three quarters, we find a similar pattern, though the magnitude becomes smaller.

In Panel B of Table 2, we rank industries based on their closeness to the 52-week high (i.e., based on the value of $MKTVLAG_{j,t}$) at the end of quarter t and examine the average value of institutional demand changes for stocks in winning and losing industries in the next four quarters. Results show that in quarter $t+1$, institutional investors increase their holdings of stocks in winning industries 1.58% more than their holding of stocks in losing industries. The value is greater than the corresponding value using the individual 52-week high strategy, 0.80%. Similarly, the number of institutional investors in winning industries increases by 5.71 more than that in losing industries, which is greater than the corresponding value using the individual 52-

Table 3
Pairwise comparison of the 52-week high and momentum strategies.

Individual momentum	Industry 52-week high	Raw return	DGTW return
Panel A			
Winner	Winner	1.59%	0.22%
	Loser	1.17%	−0.03%
	Winner–loser	0.42% (3.58)	0.25% (2.79)
Middle	Winner	1.32%	0.22%
	Loser	1.01%	−0.03%
	Winner–loser	0.31% (3.22)	0.25% (3.45)
Loser	Winner	1.31%	0.30%
	Loser	0.75%	−0.15%
	Winner − loser	0.57% (3.85)	0.45% (3.77)
Panel B			
Winner	Winner	1.59%	0.22%
	Loser	1.31%	0.30%
	Winner–loser	0.28% (1.43)	−0.08% (−1.15)
Middle	Winner	1.42%	0.13%
	Loser	0.98%	0.09%
	Winner–loser	0.44% (2.72)	0.04% (0.82)
Loser	Winner	1.17%	−0.03%
	Loser	0.75%	−0.15%
	Winner–loser	0.43% (2.51)	0.12% (1.83)
Panel C			
Winner	Winner	1.43%	0.15%
	Loser	1.25%	0.02%
	Winner–loser	0.18% (1.94)	0.12% (1.89)
Middle	Winner	1.40%	0.26%
	Loser	1.04%	0.01%
	Winner–loser	0.37% (3.64)	0.26% (3.27)
Loser	Winner	1.32%	0.32%
	Loser	0.64%	−0.22%
	Winner–loser	0.68% (4.32)	0.54% (4.21)
Panel D			
Winner	Winner	1.43%	0.15%
	Loser	1.32%	0.32%
	Winner–loser	0.11% (0.43)	−0.17% (−1.67)
Middle	Winner	1.35%	0.11%
	Loser	0.96%	0.06%
	Winner–loser	0.39% (1.71)	0.06% (0.68)
Loser	Winner	1.25%	0.02%
	Loser	0.64%	−0.22%
	Winner–loser	0.61% (2.74)	0.25% (2.74)

This table reports the average monthly returns from July 1963 through December 2009 for equally weighted portfolios. Stocks are sorted independently by past 6-month return and by the 52-week high measure. Individual momentum winners (losers) are the 30% of stocks with the highest (lowest) past 6-month return. Individual 52-week high winners (losers) are the 30% stocks with the highest (lowest) ratio of current price to 52-week high. Industry 52-week high winners (losers) are stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. All portfolios are held for 6 months. t-statistics in parentheses are based on Newey–West standard errors with three lags.

week high strategy, 2.67. We also notice that the difference is mainly in quarter $t + 1$, and there is no evidence of institutional trading in the direction of the industry 52-week high in subsequent quarters. This seems to be consistent with our later results in Table 9 that the profits to the industry 52-week high strategy is greater when investors hold the stock for 3 months instead of 6 months or 12 months.

To summarize, we find that institutional investors generally increase their holdings of stocks whose prices are close to 52-week highs and decrease their holding of stocks whose prices are far from 52-week highs. Further, the pattern is even stronger for industry 52-week high strategy than for individual 52-week high strategy. These results are consistent with the anchoring bias hypothesis.

4.2. Can return momentum explain the industry 52-week high strategy?

Because there is a positive correlation between past returns and closeness to the 52-week high, one may wonder whether the profit from the industry 52-week high strategy is caused by the momentum in stock returns. To test this, we construct the momentum strategy proposed by Jegadeesh and Titman (1993). The winners (losers) in the momentum strategy are the 30% of stocks with the highest (lowest) returns in the past six months. In the momentum strategy, we buy stocks in the winner portfolio and short stocks in the loser portfolio and hold them for six months. The return on the winner (loser) portfolio in month t is the equal-weighted return of all stocks in the portfolio.

We first perform a pairwise comparison between the momentum strategy and the industry 52-week high strategy. In Panel A of Table 3, we first group firms into winners, losers, and the middle group (the rest) based on the momentum strategy. Then within each group, we perform the industry 52-week high strategy by buying (shorting) stocks in the six industries with the highest (lowest) value of $MKTVLAG_{j,t}$. We can see that the industry 52-week high strategy is profitable in each group. In contrast, when we first group firms into winners, losers, and the middle group based on the industry 52-week high strategy in Panel B, the momentum strategy is not always profitable. In particular, the strategy is not profitable in the winner or middle group based on DGTW benchmark-adjusted returns.

Results in Panels A and B of Table 3 show that the industry 52-week high strategy is not subsumed by the return momentum effect. We also perform a pairwise comparison between individual and industry 52-week high strategies. Panels C and D report results. If we group firms into winners, losers, and the middle group based on individual 52-week high strategy, the industry 52-week high strategy is profitable in each group. When we group firms into winners, losers, and the middle group based on the industry 52-week high strategy, the individual 52-week high strategy is not always profitable. The results show that the industry 52-week high strategy is not subsumed by the individual 52-week high effect.

4.3. Comparing the five strategies simultaneously

Following Fama and MacBeth (1973) and George and Hwang (2004), we run the following regression to compare the five strategies simultaneously, while controlling for the effects of firm size and bid-ask bounce:

$$\begin{aligned} R_{i,t} = {} & b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}SIZE_{i,t-1} + b_{3jt}JH_{i,t-j} + b_{4jt}JL_{i,t-j} + b_{5jt}MH_{i,t-j} + b_{6jt}ML_{i,t-j} + b_{7jt}GH_{i,t-j} \\ & + b_{8jt}GL_{i,t-j} + b_{9jt}IdioH_{i,t-j} + b_{10jt}IdioL_{i,t-j} + b_{11jt}IndH_{i,t-j} + b_{12jt}IndL_{i,t-j} + e_{p,t}. \end{aligned} \tag{3}$$

The dependent variable, $R_{i,t}$, is the return to stock i in month t. We skip one month between the portfolio-forming month and holding period and include the month $t - 1$ return $R_{i,t-1}$ in the regression to control for the effect of bid-ask bounce. Because we form a portfolio every month and hold the portfolio for six months, the profit from a winner or loser portfolio in month t can be calculated as the sum of returns to six portfolios, each formed in one of the six past successive months $t - j$, where $j = 2, 3, \ldots, 7$ (we skip one month between portfolio formation and holding). $JH_{i,t-j}$ is a dummy variable with value 1 if stock i is included in the Jegadeesh and Titman (1993) winner portfolio in month $t - j$ (i.e., if the stock is in the top 30% based on returns from month $t - j - 6$ to month $t - j$); and 0 otherwise. Similarly, $JL_{i,t-j}$ is a dummy variable indicating whether stock i is included in the Jegadeesh and Titman (1993) loser portfolio in month $t - j$. $MH_{i,t-j}$ and $ML_{i,t-j}$ are dummy variables for Moskowitz and Grinblatt (1999) industry momentum winner and loser portfolios, and $GH_{i,t-j}$ and $GL_{i,t-j}$ are dummy variables for George and Hwang (2004) individual

Table 4
Comparison of JT, MG, individual, idiosyncratic, and industry 52-week high strategies.

	Raw return			DGTW return		
	Whole	Jan. excl.	Jan. only	Whole	Jan. excl.	Jan. only
Intercept	0.0205	0.0127	0.1073	0.0062	0.0064	0.0039
	(5.72)	(3.69)	(9.37)	(8.70)	(8.61)	(1.58)
Ri,t − 1	−0.0561	−0.0469	−0.1581	−0.0624	−0.0578	−0.1134
	(−13.51)	(−12.47)	(−7.53)	(−18.38)	(−17.76)	(−7.13)
Size	−0.0018	−0.0007	−0.0136	−0.0009	−0.0010	−0.0005
	(−4.82)	(−2.10)	(−7.80)	(−7.23)	(−7.40)	(−0.92)
JT winner dummy	0.0018	0.0016	0.0041	0.0000	−0.0006	0.0068
	(2.12)	(1.85)	(1.69)	(0.04)	(−1.51)	(4.79)
JT loser dummy	−0.0023	−0.0029	0.0045	−0.0013	−0.0010	−0.0041
	(−4.46)	(−5.39)	(1.79)	(−4.56)	(−3.58)	(−5.21)
MG winner dummy	0.0018	0.0016	0.0033	0.0014	0.0014	0.0022
	(2.35)	(2.05)	(1.37)	(2.19)	(1.98)	(1.19)
MG loser dummy	−0.0006	−0.0004	−0.0030	−0.0009	−0.0007	−0.0026
	(−0.93)	(−0.58)	(−1.38)	(−1.57)	(−1.21)	(−1.29)
Individual 52-week high winner dummy	0.0014	0.0023	−0.0096	0.0003	0.0010	−0.0076
	(1.82)	(3.17)	(−3.42)	(0.62)	(2.13)	(−4.54)
Individual 52-week high loser dummy	−0.0040	−0.0070	0.0300	−0.0018	−0.0032	0.0141
	(−2.87)	(−4.97)	(5.50)	(−2.29)	(−4.21)	(5.01)
Idiosyncratic 52-week high winner dummy	0.0001	0.0001	−0.0003	−0.0001	−0.0001	−0.0004
	(0.53)	(0.73)	(−0.79)	(−0.86)	(−0.67)	(−1.08)
Idiosyncratic 52-week high loser dummy	−0.0003	−0.0002	−0.0005	−0.0003	−0.0003	−0.0003
	(−1.69)	(−1.51)	(−1.04)	(−1.73)	(−1.66)	(−0.46)
Industry 52-week high winner dummy	0.0008	0.0007	0.0023	0.0002	0.0001	0.0012
	(1.42)	(1.25)	(1.01)	(0.47)	(0.30)	(0.64)
Industry 52-week high loser dummy	−0.0012	−0.0015	0.0023	−0.0009	−0.0011	0.0007
	(−1.90)	(−2.35)	(1.26)	(−1.57)	(−1.79)	(0.52)
JT winner dummy –	0.0040	0.0044	−0.0004	0.0013	0.0004	0.0109
JT loser dummy	(3.74)	(4.03)	(−0.13)	(2.19)	(0.73)	(6.34)
MG winner dummy –	0.0024	0.0021	0.0063	0.0023	0.0021	0.0048
MG loser dummy	(2.19)	(1.73)	(2.19)	(2.54)	(2.12)	(1.98)
Individual 52-week high winner dummy –	0.0053	0.0094	−0.0396	0.0021	0.0042	−0.0217
Individual 52-week high loser dummy	(2.63)	(4.60)	(−5.43)	(1.75)	(3.64)	(−5.45)
Idiosyncratic 52-week high winner dummy –	0.0003	0.0003	0.0002	0.0002	0.0002	−0.0001
Idiosyncratic 52-week high loser dummy	(1.76)	(1.65)	(0.42)	(0.84)	(0.88)	(−0.09)
Industry 52-week high winner dummy −	0.0020	0.0022	−0.0001	0.0011	0.0012	0.0005
Industry 52-week high loser dummy	(2.47)	(2.64)	(−0.02)	(1.60)	(1.64)	(0.22)

Each month between July 1963 and December 2009, the following cross-sectional regressions are estimated:

$$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}SIZE_{i,t-1} + b_{3jt}JH_{i,t-j} + b_{4jt}JL_{i,t-j} + b_{5jt}MH_{i,t-j} + b_{6jt}ML_{i,t-j} + b_{7jt}GH_{i,t-j} + b_{8jt}GL_{i,t-j}$$
$$+ b_{9jt}IdioH_{i,t-j} + b_{10jt}IdioL_{i,t-j} + b_{11jt}IndH_{i,t-j} + b_{12jt}IndL_{i,t-j} + e_{it}$$

where $R_{i,t}$ and $SIZE_{i,t}$ are the return and the market capitalization of stock i in month t. $IndH_{i,t-j}$ ($IndL_{i,t-j}$) is the industry 52-week high winner (loser) dummy that takes the value of 1 if the ratio of industry total capitalization in month $t-j$ to the maximum industry total capitalization achieved in months $t-j-12$ to $t-j$ for stock i is ranked in the top (bottom) 30%, and is zero otherwise. $GH_{i,t-j}$ ($GL_{i,t-j}$) is the individual 52-week high winner (loser) dummy that takes the value of 1 if the ratio of price level in month $t-j$ to the maximum price achieved in months $t-j-12$ to $t-j$ for stock i is ranked in the top (bottom) 30%, and is zero otherwise. $IdioH_{i,t-j}$ ($IdioL_{i,t-j}$) is the idiosyncratic 52-week high winner (loser) dummy that takes the value of 1 if the ratio of price level in month $t-j$ to the maximum price achieved in months $t-j-12$ to $t-j$ for stock i is ranked in the top (bottom) 30% within each industry, and is zero otherwise. $JH_{i,t-j}$ ($JL_{i,t-j}$) equals to one if stock i's return over the 6-month period ($t-j-6$, $t-j$) is in the top (bottom) 30%, and is zero otherwise; $MH_{i,t-j}$ ($ML_{i,t-j}$) equals to one if stock i's valued-weighted industry return over the 6-month period (t-$j-6$, $t-j$) is in the top (bottom) 30%, and is zero otherwise. This table reports the average of the month-by-month estimates of $\frac{1}{6}\sum_{j=2}^{7}b_{3jt}, \ldots, \frac{1}{6}\sum_{j=2}^{7}b_{12jt}$. t-Statistics in parentheses are based on Newey–West standard errors with three lags.

52-week high winner and loser portfolios. For our idiosyncratic and industry 52-week high winner and loser portfolios, we create four dummies, $IdioH_{i,t-j}$, $IdioL_{i,t-j}$, $IndH_{i,t-j}$, and $IndL_{i,t-j}$.

Following George and Hwang (2004), we first run separate cross-sectional regressions of Eq. (3) for each $j = 2, \ldots, 7$. Then the total return in month t of a portfolio is the average over $j = 2, \ldots, 7$. For example, the

Table 5
Profits of the individual 52-week high strategy of firms with different industry betas and R-squares.

	Raw return			DGTW return		
	T1-low	T2	T3-high	T1-low	T2	T3-high
Panel A: rank by industry beta						
Winner	1.31%	1.37%	1.35%	0.05%	0.13%	0.13%
	(7.40)	(6.28)	(4.84)	(0.58)	(3.73)	(2.87)
Loser	1.28%	1.03%	0.55%	0.24%	0.10%	−0.22%
	(3.61)	(2.73)	(1.20)	(3.89)	(1.99)	(−1.98)
Winner–loser	0.03%	0.34%	0.80%	−0.19%	0.03%	0.34%
	(0.13)	(1.54)	(2.91)	(−2.07)	(0.37)	(3.30)
Panel B: rank by R-square						
Winner	1.39%	1.39%	1.27%	0.09%	0.12%	0.11%
	(6.94)	(6.29)	(5.63)	(1.19)	(3.32)	(3.32)
Loser	1.43%	0.85%	0.47%	0.36%	−0.04%	−0.23%
	(3.28)	(2.04)	(1.23)	(4.11)	(−0.58)	(−2.66)
Winner–loser	−0.04%	0.54%	0.80%	−0.27%	0.16%	0.33%
	(−0.14)	(2.13)	(3.53)	(−2.08)	(1.80)	(3.56)

This table reports the average monthly portfolio returns for individual 52-week high strategy for each tercile which is ranked by the R-square or industry beta ($\beta_{ind,i}$)from the regression $R_{i,t} = a_i + \beta_{ind,i} R_{ind,t} + e_{i,t}$, where $R_{i,t}$ is the return of stock i on day t and $R_{ind,t}$ is the value-weighted stock return of stock i's industry. We run this regression at the end of each month for each stock, using returns in the past year. Each month, stocks are sorted by R-square or industry beta ($\beta_{ind,i}$) from this regression. Individual 52-week high winner (loser) portfolio is the equal-weighted portfolio of the 30% of stocks with the highest (lowest) ratio of current price to 52-week high. The monthly returns are from July 1963 to December 2009. t-Statistics in parentheses are based on Newey–West standard errors with three lags.

month t return to the Jegadeesh and Titman (1993) individual momentum winner portfolio is $\frac{1}{6}\sum_{j=2}^{7} b_{3jt}$. We then report in Table 4 the time-series averages of these values and the associated t-statistics when either the raw return or the DGTW benchmark-adjusted return is the dependent variable. Profits from the five investment strategies are reported in the bottom panel. We also run regressions excluding Januarys and in Januarys only.

When we use raw return as the dependent variable, the industry 52-week high strategy generates a return of 0.20% after controlling for the other four investing strategies, indicating that the profits from the industry 52-week high are above and beyond those from the other four strategies. Results excluding Januarys are similar. The third column shows that, in Januarys, while the individual 52-week high strategy loses money, the industry or the idiosyncratic 52-week high strategy generates essentially zero profit. The results using DGTW benchmark-adjusted returns are similar.

4.4. Is the 52-week high effect driven by industry or firm-specific information?

So far, our results show that the industry 52-week high strategy is more profitable than the idiosyncratic 52-week high strategy. This suggests that the 52-week high effect is mainly driven by investor underreaction to industry instead of firm-specific information. If this is true, then the 52-week high effect documented by George and Hwang (2004) should be more pronounced among firms whose values are influenced more by industry information and less by firm-specific information, i.e., stocks with high industry betas and high factor model R-squares.

To estimate industry beta and R-square, we run the following regression for each stock i using daily stock return data in the past 12 months:

$$R_{i,t} = a_i + \beta_{ind,i} R_{ind,t} + e_{i,t}, \tag{4}$$

where $R_{i,t}$ is the return on stock i at day t, and $R_{ind,t}$ is the value-weighted return of all stocks in stock i's industry at day t. The industry portfolio is constructed without stock i. Industry beta is the estimated value of $\beta_{ind,i}$, and R-square is the adjusted R-square from the regression. At the end of each month, we repeat the regression and rank stocks based on industry beta and R-square. We then examine the profits to the individual 52-week high strategy in each industry beta tercile and R-square tercile.

Panel A of Table 5 shows that the profit to the individual 52-week high strategy is 0.03% per month among firms with the lowest industry betas. The profit increases to 0.34% in the middle group and 0.80% among firms with the highest industry betas. Results based on DGTW benchmark-adjusted returns show a similar pattern. The 52-week high effect is strongest among high industry beta firms and weakest among low industry beta firms.

Panel B of Table 5 shows that the profit to the individual 52-week high strategy increases with a firm's R-square. The profit among firms in the lowest tercile of R-square is −0.04% per month, though not statistically significant. The profit increases to 0.54% in the middle group and 0.80% among firms with the highest R-squares. If we use DGTW benchmark-adjusted returns, the individual 52-week high strategy actually loses 0.27% per month among firms with the lowest R-squares, and the negative profit is statistically different from zero at the 5% level. The profit is 0.16% in the middle group and 0.33% among firms with the highest R-squares.

To summarize, results in Table 5 indicate that the 52-week high effect is mainly driven by industry information instead of firm-specific information. The 52-week high effect documented by George and Hwang (2004) is more pronounced among firms with high industry betas and high R-squares.

4.5. Industry price informativeness and the industry 52-week high effect

If the profits from the industry 52-week high strategy are indeed driven by the anchoring bias of investors, we would expect the bias to be stronger among industries whose valuations are harder to determine. Therefore, the industry 52-week high effect should be more (less) pronounced among industries with less (more) informative prices. To test this, we use five industry price informativeness measures below:

1. Average firm size, defined as the average market capitalization of firms in the industry at the end of the month of the portfolio formation. It is well known that large firms have more informative prices than small firms (e.g., Fama and French, 1993).
2. Average firm age, measured as the number of months since the stock is publicly traded, averaged over all firms in the industry. Availability of public trading history may reduce the information asymmetry between the firm and outside investors (e.g., Stambaugh, 1997). Therefore, older firms should have more informative prices than younger firms.
3. Average price impact. For each firm, price impact is measured by the absolute daily return divided by the daily dollar volume of trade (in millions), averaged over the past twelve months, similar to the definition in Amihud (2002). It measures how easily investors can liquidate a stock without severely affecting the price. Firms with less informative prices generally have high price impacts (e.g., Amihud, 2002). Industry price impact is the average value of price impact among all firms in the industry.
4. Average analyst coverage, defined as the industry average number of analysts following the firm. Firms with more analyst coverage should have more informative prices (e.g., Womack, 1996).
5. Average institutional ownership, defined as the industry average fraction of shares held by institutions who file the 13 F form with the Securities and Exchange Commission. Firms with more institutional ownership may have less information asymmetry (Gompers and Metrick, 2001).

We divide industries into three groups (6, 8, and 6 industries in the three groups) based on each of the above measures and evaluate the profits to the industry 52-week high strategy in each group (winner and loser industries are the top and bottom two industries). Table 6 reports the results.

Panel A of Table 6 shows that the profit to the industry 52-week high strategy is 0.48% per month among industries with small firms (the bottom 6 industries based on average firm size). In contrast, the profit is 0.37% among industries with mid-sized firms and 0.35% among industries with large firms. Results based on DGTW benchmark-adjusted returns show a similar pattern.

Panel B of Table 6 shows that the profit to the industry 52-week high strategy decreases with average firm age. The profit among firms in the bottom 6 industries is 0.55% per month. It is 0.46% in the middle group and 0.07% in the top group. If we use DGTW benchmark-adjusted returns, the profit is 0.36% per month among industries with young firms and 0.06% among industries with old firms.

Panels C, D, and E report results based on average price impact, average analyst coverage, and average institutional ownership, respectively. They all show the same pattern. The industry 52-week high strategy

Table 6
Profits of the industry 52-week high strategy for industries with different price informativeness measures.

Average firm size	Raw return			DGTW return		
	Winner	Loser	W–L	Winner	Loser	W–L
Panel A: average firm size and industry 52-week high (July 1963–December 2009)						
T1 − Small	1.43%	0.95%	0.48%	0.25%	−0.15%	0.40%
	(4.87)	(3.08)	(4.18)	(4.43)	(−2.12)	(4.06)
T2	1.45%	1.09%	0.37%	0.28%	0.03%	0.25%
	(5.12)	(3.59)	(2.2)	(3.94)	(0.39)	(2.22)
T3 − Large	1.27%	0.92%	0.35%	0.20%	−0.07%	0.26%
	(4.93)	(3.12)	(2.54)	(3.32)	(−0.86)	(2.53)
Panel B: average firm age and industry 52-week high (July 1963–December 2009)						
T1 − Small	1.45%	0.89%	0.55%	0.27%	−0.09%	0.36%
	(4.75)	(2.81)	(3.56)	(4.17)	(−1.20)	(3.24)
T2	1.44%	0.99%	0.46%	0.30%	−0.09%	0.39%
	(5.07)	(3.23)	(3.67)	(5.07)	(−1.22)	(3.95)
T3 − Large	1.16%	1.10%	0.07%	0.03%	−0.03%	0.06%
	(5.32)	(4.00)	(0.48)	(0.39)	(−0.36)	(0.5)
Panel C: average price impact and industry 52-week high (July 1963–December 2009)						
T1 − Small	1.21%	0.97%	0.24%	0.09%	−0.03%	0.12%
	(5.05)	(3.44)	(1.41)	(1.27)	(−0.31)	(1.05)
T2	1.49%	1.01%	0.48%	0.31%	−0.05%	0.35%
	(4.88)	(3.23)	(3.61)	(4.03)	(−0.67)	(3.28)
T3 − Large	1.45%	1.01%	0.45%	0.28%	−0.08%	0.36%
	(4.93)	(3.18)	(3.79)	(4.72)	(−0.98)	(3.67)
Panel D: average analyst coverage and industry 52-week high (January 1984–December 2009)						
T1 − Small	1.41%	0.87%	0.54%	0.29%	−0.07%	0.36%
	(3.92)	(2.31)	(2.55)	(3.76)	(−0.63)	(2.37)
T2	1.38%	0.91%	0.47%	0.26%	−0.12%	0.39%
	(3.86)	(2.42)	(2.51)	(3.40)	(−1.41)	(2.99)
T3 − Large	1.27%	1.10%	0.17%	0.17%	−0.06%	0.23%
	(3.89)	(2.89)	(1.13)	(2.14)	(−0.48)	(1.84)
Panel E: Average institutional ownership and industry 52-week high (January 1980–December 2009)						
Average IO	Raw ret			DGTW ret		
	Winner	Loser	W–L	Winner	Loser	W–L
T1 − Small	1.22%	0.96%	0.27%	0.24%	−0.01%	0.24%
	(3.08)	(2.38)	(1.29)	(2.61)	(−0.06)	(1.55)
T2	1.30%	0.79%	0.50%	0.31%	−0.15%	0.45%
	(3.38)	(1.78)	(2.19)	(3.30)	(−1.16)	(2.86)
T3 − Large	1.15%	1.06%	0.09%	0.18%	0.04%	0.15%
	(3.22)	(2.71)	(0.51)	(1.51)	(0.29)	(0.91)

This table reports the average monthly portfolio returns for the industry 52-week high strategy for industries with different price informativeness: average firm size, average firm age, average price impact, average analyst coverage, and average institutional ownership. We firs rank industries into three groups (6, 8, and 6 industries in each group) based on each of these measures. Industry 52-week high winners (losers) are the top (bottom) 2 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. All portfolios are held for 6 months. *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

is more profitable among industries with high information asymmetry (industries with high average price impact, low average analyst coverage, and low average institutional ownership). The results in Table 6 are consistent with the notion that the industry 52-week high effect is driven by investors' anchoring bias.

4.6. Portfolio rebalancing and the industry 52-week high strategy

So far, we have followed the prior literature (e.g., George and Hwang, 2004; Jegadeesh and Titman, 1993; Moskowitz and Grinblatt, 1999) and formed equal-weighted portfolios when designing our strategies. One criticism is that since we hold our portfolios for six months, we need to rebalance our portfolios at the end of each month in order to keep them equal-weighted. The rebalancing can be potentially costly if the transaction costs are high, and it is not clear whether our strategies are still profitable after transaction costs. We

Table 7
Portfolio rebalancing and individual, idiosyncratic, and industry 52-week high strategies.

	Raw return			DGTW return		
	Winner	Loser	Winner–loser	Winner	Loser	Winner–loser
Panel A: monthly returns without rebalancing						
Individual	1.27%	0.43%	0.84%	0.08%	−0.01%	0.09%
	(7.85)	(1.46)	(4.81)	(3.64)	(−0.13)	(1.51)
Idiosyncratic	1.23%	0.55%	0.67%	0.08%	0.02%	0.05%
	(7.25)	(2.01)	(4.94)	(4.17)	(0.77)	(1.26)
Industry	1.20%	0.67%	0.53%	0.20%	−0.12%	0.33%
	(5.69)	(3.06)	(5.69)	(5.34)	(−2.45)	(4.39)
Panel B: monthly value-weighted average portfolio return among small stocks (Size ≤ 25 percentile)						
Individual	1.58%	0.69%	0.89%	0.06%	−0.27%	0.33%
	(6.48)	(1.64)	(3.66)	(1.33)	(−5.1)	(3.76)
Idiosyncratic	1.50%	0.76%	0.74%	0.04%	−0.25%	0.30%
	(5.95)	(1.87)	(3.60)	(1.02)	(−5.70)	(3.90)
Industry	1.41%	0.71%	0.70%	0.05%	−0.33%	0.38%
	(3.90)	(2.07)	(4.61)	(0.90)	(−5.53)	(4.10)

Panel A reports returns to individual, idiosyncratic, and industry 52-week high strategies if we do not rebalance the portfolio. Each month, we form portfolios based on individual, idiosyncratic, and industry 52-week high measures and hold the portfolios for six months without rebalancing. Then we calculate the buy and hold six-month cumulative raw return and the buy and hold six-month cumulative abnormal return, where the abnormal return is the six-month cumulative raw return minus the six month cumulative raw return on the size/book-to-market ratio/momentum portfolio. Panel B reports monthly value-weighted average portfolio returns for small stocks. Each month, we form portfolios based on the 52-week high measures and then calculate monthly value-weighted average small stock returns for each portfolio. Small stocks are stocks with size below 25 percentile of all stocks. All portfolios are held for 6 months. The sample includes all stocks on CRSP from July 1963 through December 2009; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

address the implementability of the industry 52-week high strategy related to the rebalancing of the portfolio in this subsection.

First, we consider a modified industry 52-week high strategy that does not require monthly portfolio rebalancing. Specifically, at the end of each month t, we buy an equal-weighted portfolio of stocks in the six industries with the highest value of $MKTVLAG_{j,t}$, and short the same dollar amount of an equal-weighted portfolio of stocks in the six industries with the lowest value of $MKTVLAG_{j,t}$. We then hold the portfolio for six months without rebalancing. Therefore, at the end of each month, the portfolio is neither equal-weighted nor value-weighted. To calculate the average monthly return of such a strategy, we first calculate the six-month cumulative buy-and-hold raw return of each stock in each portfolio. The cumulative profit of the modified industry 52-week high strategy ($CRET$) is the mean cumulative return of all stocks in the long portfolio minus that of all stocks in the short portfolio. The monthly profit of the modified industry 52-week high strategy is then $(1 + CRET)^{1/6} - 1$.

To calculate the abnormal return of the modified industry 52-week high strategy, we form 125 portfolios at the end of month t based on size, book-to-market ratio, and momentum. The six-month cumulative abnormal return of each stock is the cumulative raw return minus the cumulative return on the portfolio to which the stock belongs. The cumulative abnormal return of the modified industry 52-week high strategy ($ACRET$) is the mean abnormal cumulative return of all stocks in the long portfolio minus that of all stocks in the short portfolio. The monthly abnormal return of the modified industry 52-week high strategy is then $(1 + ACRET)^{1/6} - 1$. The modified individual and idiosyncratic 52-week high strategies are similarly defined.

Panel A of Table 7 shows that the modified industry 52-week high strategy that does not require monthly rebalancing is still profitable, with an average monthly return of 0.53%. The average DGTW benchmark-adjusted abnormal return of the strategy is 0.33% per month, which is greater than the abnormal returns on the modified individual or idiosyncratic 52-week high strategy.

We now consider a second way to address the rebalancing concern. In Table 6, we have seen that the industry 52-week high strategy is more profitable among small firms. If investors want to implement the industry 52-week high strategy, they can always focus on small stocks and form value-weighted portfolios. This way, investors do not have to worry about portfolio rebalancing. To see if such a strategy is still profitable, we buy a value-weighted portfolio of small stocks in the six industries with the highest values of $MKTVLAG_{j,t}$

Table 8
Individual, idiosyncratic, and industry 52-week high strategies in different time periods.

		Raw return			DGTW return		
		Winner	Loser	W–L	Winner	Loser	W–L
July 63–Dec 78	Individual	1.16%	1.09%	0.08%	0.07%	−0.06%	0.13%
		(2.86)	(1.58)	(0.23)	(1.80)	(−0.78)	(1.21)
	Idiosyncratic	1.17%	1.11%	0.06%	0.09%	−0.06%	0.15%
		(2.75)	(1.67)	(0.21)	(2.64)	(−0.98)	(1.75)
	Industry	1.36%	1.03%	0.33%	0.17%	0.00%	0.18%
		(2.78)	(1.91)	(2.12)	(2.82)	(−0.03)	(1.65)
Jan 79–Dec 94	Individual	1.65%	0.78%	0.87%	0.14%	0.05%	0.09%
		(4.68)	(1.36)	(2.85)	(3.61)	(0.71)	(0.89)
	Idiosyncratic	1.56%	0.92%	0.64%	0.11%	0.10%	0.00%
		(4.29)	(1.65)	(2.44)	(3.17)	(1.51)	(0.05)
	Industry	1.48%	0.92%	0.55%	0.22%	−0.09%	0.31%
		(3.44)	(2.1)	(3.42)	(4.59)	(−1.18)	(2.93)
Jan 95–Dec 09	Individual	1.22%	0.89%	0.34%	0.11%	0.10%	0.01%
		(3.71)	(1.07)	(0.55)	(1.46)	(0.68)	(0.05)
	Idiosyncratic	1.20%	0.95%	0.25%	0.09%	0.11%	−0.03%
		(3.29)	(1.28)	(0.53)	(1.63)	(1.13)	(−0.18)
	Industry	1.34%	0.85%	0.50%	0.33%	−0.13%	0.45%
		(2.50)	(1.47)	(1.60)	(2.90)	(−0.95)	(2.22)
Exclude 98 99 00 08 09	Individual	1.46%	0.99%	0.47%	0.11%	0.01%	0.10%
		(6.82)	(2.54)	(2.07)	(4.13)	(0.26)	(1.40)
	Idiosyncratic	1.42%	1.06%	0.36%	0.10%	0.03%	0.07%
		(6.30)	(2.90)	(1.93)	(5.03)	(0.85)	(1.25)
	Industry	1.42%	1.06%	0.36%	0.18%	−0.03%	0.22%
		(5.45)	(3.56)	(3.19)	(5.49)	(−0.71)	(3.17)

This table reports the average monthly portfolio returns for individual, idiosyncratic, and industry 52-week high strategies in four time periods. All portfolios are held for 6 months. The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks on CRSP; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

and short the same dollar amount of a value-weighted portfolio of small stocks in the six industries with the lowest values of $MKTVLAG_{j,t}$. Small stocks are defined as the 25% of stocks with the lowest values of market capitalization at the end of month t. Similarly, we calculate the profit of the individual and idiosyncratic 52-week high strategies among small stocks using value-weighted portfolios.

Panel B of Table 7 shows that the industry 52-week high strategy is still profitable if we focus on small stocks and use value-weighted portfolios, with an average monthly return of 0.70%. The average DGTW benchmark adjusted abnormal return of the strategy is 0.38% per month. Both the idiosyncratic and individual 52-week high strategies produce similar magnitudes of profits compared to the industry 52-week high strategy among small stocks.

To summarize, even though we follow the literature and form equal-weighted portfolios in our industry 52-week high strategy, which requires monthly rebalancing of the portfolio, our results still hold if we modify our strategy so that portfolio rebalancing is not necessary.

5. Additional robustness tests

In this section, we perform some additional robustness tests regarding our main findings.

5.1. Sample periods

To test if our results hold over different time periods, we divide our sample period into three sub-periods: July 1963 to December 1978, January 1979 to December 1994, and January 1995 to December 2009, so that

Table 9
Individual, idiosyncratic, and industry 52-week high strategies with alternative holding periods.

		Raw return			DGTW return		
		Winner	Loser	W–L	Winner	Loser	W–L
Panel A: hold the portfolio for 3 months							
Whole	Individual	1.35%	0.91%	0.44%	0.09%	0.04%	0.05%
		(6.43)	(2.24)	(1.74)	(2.86)	(0.81)	(0.57)
	Idiosyncratic	1.30%	1.02%	0.28%	0.07%	0.10%	−0.04%
		(5.88)	(2.68)	(1.35)	(2.61)	(2.37)	(−0.57)
	Industry	1.49%	0.82%	0.67%	0.32%	−0.14%	0.46%
		(5.33)	(2.76)	(5.33)	(6.39)	(−2.39)	(4.97)
Jan excluded	Individual	1.22%	0.03%	1.19%	0.14%	−0.08%	0.23%
		(5.70)	(0.07)	(4.54)	(4.63)	(−1.55)	(2.83)
	Idiosyncratic	1.16%	0.19%	0.97%	0.12%	−0.01%	0.13%
		(5.16)	(0.50)	(4.74)	(4.81)	(−0.31)	(2.22)
	Industry	1.12%	0.32%	0.80%	0.30%	−0.19%	0.49%
		(4.01)	(1.07)	(5.19)	(6.18)	(−3.06)	(5.11)
Jan only	Individual	2.80%	10.67%	−7.87%	−0.53%	1.47%	−1.99%
		(3.99)	(6.38)	(−5.68)	(−4.30)	(4.82)	(−5.08)
	Idiosyncratic	2.88%	10.26%	−7.38%	−0.50%	1.35%	−1.85%
		(4.01)	(6.52)	(−6.01)	(−3.85)	(5.26)	(−5.21)
	Industry	5.69%	6.44%	−0.75%	0.49%	0.40%	0.10%
		(6.03)	(5.58)	(−1.47)	(3.16)	(2.42)	(0.40)
Panel B: hold the portfolio for 12 months							
Whole	Individual	1.29%	1.04%	0.25%	0.09%	0.10%	−0.01%
		(6.09)	(2.63)	(1.08)	(2.88)	(1.54)	(−0.11)
	Idiosyncratic	1.27%	1.08%	0.19%	0.09%	0.09%	−0.01%
		(5.65)	(2.92)	(1.02)	(3.64)	(1.92)	(−0.13)
	Industry	1.33%	1.01%	0.32%	0.18%	−0.03%	0.21%
		(4.83)	(3.40)	(2.90)	(4.76)	(−0.57)	(2.86)
Jan excluded	Individual	1.13%	0.19%	0.94%	0.14%	−0.04%	0.18%
		(5.24)	(0.49)	(4.02)	(4.48)	(−0.73)	(2.1)
	Idiosyncratic	1.09%	0.28%	0.81%	0.13%	−0.03%	0.16%
		(4.80)	(0.78)	(4.62)	(5.68)	(−0.62)	(2.54)
	Industry	0.94%	0.53%	0.41%	0.16%	−0.06%	0.22%
		(3.41)	(1.80)	(3.54)	(4.4)	(−1.24)	(3.01)
Jan only	Individual	3.11%	10.48%	−7.37%	−0.47%	1.67%	−2.14%
		(4.23)	(6.62)	(−6.02)	(−4.49)	(5.4)	(−5.53)
	Idiosyncratic	3.23%	9.95%	−6.72%	−0.45%	1.46%	−1.91%
		(4.23)	(6.67)	(−6.36)	(−4.7)	(5.43)	(−5.55)
	Industry	5.65%	6.37%	−0.72%	0.40%	0.36%	0.04%
		(6.45)	(5.59)	(−1.88)	(2.89)	(4.34)	(0.23)

This table reports the average monthly portfolio returns for individual, idiosyncratic, and industry 52-week high strategies. The portfolios are held for 3 months (Panel A) or 12 months (Panel B). The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks on CRSP; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

each sub-period has roughly the same length. We compare the profits to the three 52-week high strategies in each sub-period, using both raw returns and DGTW benchmark-adjusted returns.

Table 8 shows that from July 1963 to December 1978, the individual and idiosyncratic 52-week high strategies generate 0.08% and 0.06% per month, which are both insignificantly different from zero. In contrast, the industry 52-week high strategy generates 0.33% per month, which is statistically significantly different from zero at the 5% level. When we use DGTW benchmark-adjusted returns, both the industry and idiosyncratic 52-week high strategies generate significant profits, whereas the profit to the individual 52-week high strategy is not statistically significant.

From January 1979 to December 1994, when we use raw returns, all three 52-week high strategies generate significant profits. However, when we use DGTW benchmark-adjusted returns, only the industry 52-week high strategy generates significant profits. From January 1995 to December 2009, the industry 52-week high strategy generates significant profits based on DGTW benchmark-adjusted returns, though the profit based on raw returns is not statistically significant ($t = 1.60$). In contrast, the idiosyncratic and individual 52-week high strategies generate no significant profits when we use either raw returns or the DGTW benchmark-adjusted returns.

The above results show that in each sub-period, the industry 52-week high strategy generates greater profits than the idiosyncratic 52-week high strategy. We also explore whether our results are driven by extreme market conditions. Specifically, during the Internet bubble period, many stocks had very high stock prices and prices at or close to their 52-week highs. In contrast, during the recent financial crisis, many stocks have very low prices that are far from their 52-week highs. We test if our results are robust to the exclusion of the following two periods: 1998–2000 and 2008–2009.

Results at the bottom of Table 8 show that our results hold even after excluding the Internet bubble period and the recent financial crisis period. When we use raw returns, all three 52-week high strategies generate significant profits. When we use DGTW benchmark-adjusted returns, the industry 52-week high strategy continue to generate significant profits, whereas the profits associated with the other two strategies are not statistically significant.

5.2. Changing the holding period to three or twelve months

In all previous tests, we follow George and Hwang (2004) and hold the portfolios for six months after forming the winner and loser portfolios. In this subsection, we examine whether our results hold if we hold the portfolio for three or twelve months. Results are reported in Table 9.

Panel A of Table 9 shows that if we hold the portfolios for three months instead of six months, the individual 52-week high strategy generates 0.44% per month, whereas the industry 52-week high strategy generates 0.67% per month. The idiosyncratic 52-week high strategy does not generate significant profits. When we use DGTW benchmark-adjusted returns, the industry 52-week high strategy generates significant profits, whereas the other two strategies do not. By looking at profits excluding Januarys and in Januarys only, we can see that there are large negative returns for the individual and the idiosyncratic 52-week high strategies in Januarys, whereas the profits to the industry 52-week high are insignificantly different from zero in Januarys.

Panel B of Table 9 shows that if we hold the portfolios for twelve months, the results are qualitatively similar to those in Panel A of Table 9 and those in Table 1. Overall, Table 9 shows that if we hold our portfolios for three or twelve months instead of six months, our main results are unchanged.

5.3. Alternative industry classification

We use the industry classification method from Moskowitz and Grinblatt (1999) in the paper. In this subsection, we examine whether our results hold if we use an alternative industry classification method, namely, the 3-digit North American Industry Classification System (NAICS) codes.[8]

Results in Table 10 are similar to those in Table 1, where we use the 20 industries from Moskowitz and Grinblatt (1999). Panel A of Table 10 shows that the industry 52-week high strategy is more profitable than both the individual and idiosyncratic 52-week high strategies, especially when we use DGTW benchmark-adjusted returns. By looking at profits excluding Januarys and in Januarys only in Panels B and C, we can see that there are large negative returns for the individual and idiosyncratic 52-week high strategies in January, whereas the profits to the industry 52-week high are insignificantly different from zero in January.

Overall, Table 10 shows that if we use the 3-digit NAICS codes to define industries, our main results are unchanged.

[8] NAICS is used by business and government to classify business establishments according to the type of economic activity in North America. It has largely replaced the older SIC system.

Table 10
Profits from individual, idiosyncratic, and industry 52-week high strategies when we use 3-digit NAICS to classify industries.

	Raw return			DGTW return		
	Winner	Loser	Winner–Loser	Winner	Loser	Winner–Loser
Panel A: all months included						
Individual	1.35%	0.92%	0.43%	0.11%	0.03%	0.08%
	(6.41)	(2.88)	(1.74)	(3.53)	(0.50)	(0.94)
Industry	1.23%	0.76%	0.47%	0.08%	−0.33%	0.40%
	(4.26)	(2.32)	(3.43)	(1.67)	(−4.37)	(3.95)
Idiosyncratic	1.13%	1.11%	0.02%	−0.10%	0.06%	−0.16%
	(4.82)	(2.93)	(0.10)	(−3.81)	(0.98)	(−2.21)
Industry − Idio			0.46%			0.57%
			(2.36)			(4.08)
Idio − Individual			−0.42%			−0.24%
			(−4.48)			(−4.03)
Industry − Individual			0.04%			0.33%
			(0.17)			(2.35)
Panel B: excluding January						
Individual	1.21%	0.05%	1.16%	0.16%	−0.10%	0.26%
	(5.63)	(0.12)	(4.51)	(5.17)	(−1.75)	(3.08)
Industry	0.81%	0.20%	0.61%	0.04%	−0.37%	0.41%
	(2.79)	(0.61)	(4.22)	(0.92)	(−4.84)	(4.02)
Idiosyncratic	0.94%	0.32%	0.63%	−0.06%	−0.05%	−0.01%
	(3.96)	(0.84)	(3.43)	(−2.42)	(−0.87)	(−0.16)
Industry − Idio			−0.02%			0.42%
			(−0.10)			(3.19)
Idio − Individual			−0.53%			−0.27%
			(−5.24)			(−4.28)
Industry − Individual			−0.55%			0.16%
			(−2.51)			(1.18)
Panel C: January only						
Individual	2.95%	10.57%	−7.62%	−0.45%	1.45%	−1.90%
	(4.09)	(6.42)	(−5.63)	(−3.84)	(4.71)	(−4.84)
Industry	5.92%	6.96%	−1.05%	0.47%	0.16%	0.31%
	(6.21)	(5.04)	(−1.75)	−2.4	(0.75)	(0.98)
Idiosyncratic	3.22%	9.98%	−6.76%	−0.52%	1.33%	−1.85%
	(4.14)	(6.21)	(−5.44)	(−4.00)	(3.43)	(−3.84)
Industry − Idio			5.72%			2.16%
			(5.83)			(3.21)
Idio − Individual			0.86%			0.05%
			(2.12)			(0.30)
Industry − Individual			6.57%			2.21%
			(6.57)			(3.65)

This table reports the average monthly portfolio returns from July 1963 through December 2009 for individual, idiosyncratic, and industry 52-week high strategies when we use 3-digit NAICS to classify industries. All portfolios are held for 6 months. The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 30% industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks in CRSP; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

6. Conclusion

In this paper, we find that the 52-week high effect (George and Hwang, 2004) cannot be explained by standard risk factors. We find that the effect is more consistent with investor underreaction caused by anchoring bias: the presumably more sophisticated institutional investors suffer less from this bias and buy (sell) stocks close to (far from) their 52-week highs. Further, the 52-week high effect is mainly driven by investor underreaction to industry information. The extent of underreaction is more for positive than for negative industry information. We also find that the 52-week high strategy works best among stocks with high factor model R-squares and high industry betas (i.e., stocks whose values are most affected by industry factors and least affected by firm-specific information).

We design an idiosyncratic 52-week high trading strategy to buy stocks with prices close to their 52-week highs and short the same dollar amount of stocks in the same industry with prices far from their 52-week highs. We also design an industry 52-week high trading strategy to buy industries whose total market capitalizations are close to their 52-week highs and short industries whose total market capitalizations are far from their 52-week highs. We find that the industry 52-week high strategy generates a monthly return of 0.46% from 1963 to 2009, higher than the 0.32% from the idiosyncratic 52-week high strategy, and also slightly higher than the profit generated from the individual 52-week high strategy proposed by George and Hwang (2004) in the same period.

Also consistent with the anchoring bias effect, our industry 52-week high trading strategy is most profitable among industries in which stock prices are hard to value, namely, industries with smaller and younger firms, industries with large price impacts, industries with low analyst coverage, and industries with relatively low institutional ownership. Our results hold after controlling for individual and industry momentum effects.

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