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Cranes among chickens: The general-attention-grabbing effect of daily price limits in China's stock market

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ABSTRACT

This paper examines the general-attention-grabbing effect of daily price limits in China's stock market. We show that stocks with large exposure to daily price limits attract more investor attention and have lower future returns. The exposure is measured empirically through the absolute beta with respect to the daily proportion of stocks that hit price limits. The general-attention-grabbing effect is not solely caused by stocks that recently hit price limits, is not subsumed by market volatility exposure, and does not reflect other stock market characteristics. Moreover, the effect is stronger among stocks that are heavily invested in by retail investors.

1. Introduction

Daily price limits, as a market-stabilizing mechanism, are common on major stock exchanges across the world.[1] The purpose of daily price limits is to avoid violent fluctuations in the stock market, but their salient nature nonetheless attracts investors' attention. It is well documented in the literature that investors allocate their limited attention to stocks that hit upper price limits and generate attention-induced buying pressure, which destabilizes financial markets (e.g., Seasholes and Wu, 2007; Chen et al., 2019; Jiang et al., 2021; Cai et al., 2022). Although hitting price limits in China's stock market is widely studied as a measure of investors' attention, little research has analyzed the spillover effects of attention-grabbing by daily price limits. In this paper, we investigate the general-attention-grabbing effect of daily price limits and explore its asset-pricing implications. We choose China's stock market as our testing venue because it is the largest stock market that adopts daily price limits and is well known for its uninformed speculative trading.

In fact, investors' attention can be attracted not only to stocks that hit daily price limits but also to stocks with high exposure to daily price limits. For example, when some stocks hit price limits, the investment media and investors' forums often list the "related stocks", which may have some "connectedness" with the price limit-hitting stocks. Therefore, the general-attention-grabbing effect of daily price limits is similar to an old Chinese proverb, "cranes among chickens", in which attention to price-limit-hitting stocks (cranes) may spill over to "related stocks" (chickens). As a result, related stocks also experience an attention shock and short-term buying pressure.

The challenge in empirically examining the general-attention-grabbing effect is to identify stocks that are potentially related to stocks that hit price limits (denoted as limits-hitters, or LHs hereafter). Investment media select related stocks in all dimensions, such as firms in the same industry, corporations with similar customers or suppliers, companies located in the same city, firms held by the same funds, or even stocks with similar names.[2] In some cases, it is impossible to identify all the selection criteria that have been used. For example, on May 12, 2020, the stock price of Hunan Mendale Hometextile Co., Ltd. hit daily price limits because the company signed a contract with Ya Wei, the largest individual website salesperson on the Taobao platform, which was classified as a new business model, called customer-to-manufacturer (C2M), by some investment media. Because the concept of customer-to-

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[1] For example, Deb et al. (2010) document that 41 stock exchanges out of 58 countries impose price limits.

[2] See, for example, a discussion of "concept stocks" in China at http://www.yjcf360.com/gushifocus/871978.htm.

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manufacturer (C2M) is brand new, no one knows how to define the scope of "related stocks". Nonetheless, investment media reported 10 "related companies" whose share prices rose sharply.[3] The actual criteria for selecting related stocks can be even more complicated because they are time varying and opaque to retail investors and researchers.

In this paper, we solve this problem by constructing a general-attention-grabbing measure, following Kelly and Jiang (2014). First, on each day, we calculate the proportion of LHs by dividing the number of LHs to the total number of trading stocks on that day. Next, we calculate the monthly absolute price limits beta (APL beta hereafter) for each stock. In each month, we regress daily returns of each stock on the proportion of LHs and Fama-French and Carhart (1997) four-factors' returns, and the APL beta is calculated as the absolute value of the coefficient on the proportion of LHs as our measure for the general-attention-grabbing effect.[4] The APL beta is helpful for us to search for stocks that are sensitive to daily price limits. For example, because of enterprise reorganization, Xinjiang Tianshan Cement Co., Ltd. became a new leader in China's cement industry and hit the daily price limits on July 17, 2020. Based on the measure of the general-attention-grabbing effect proposed in our paper, we find that Dinghan Technology had a high APL beta in July 2020. We further verify that Dinghan Technology was indeed one of the "related stocks" reported in various news items about Xinjiang Tianshan Cement Co., Ltd.[5]

After constructing APL beta, we use this measure to test the general-attention-grabbing effect of daily price limits. First, we follow Barber and Odean (2008) and check the relationship between APL beta and the intensity of investors' attention. We find that stocks with a high APL beta have higher risk-adjusted contemporaneous returns, higher buy-sell imbalances, higher turnover, and higher trading volume. The empirical results indicate that stocks with a high APL beta indeed attract more investor attention.

Next, we explore the cross-sectional return predictability of the general-attention-grabbing effect. Specifically, we conduct a portfolio sorting analysis and sort stocks on their APL beta. We conjecture that stocks with higher APL beta would have lower future returns because they attract more investors' attention, so they are more likely to be overpriced due to the buying pressure of retail investors.[6] The empirical results confirm our conjecture. For example, a long-short portfolio that buys stocks with low APL beta and sells stocks with high APL beta earns a Fama-French six-factor (2018) and Amihud (2002) illiquidity factor alpha of 1.14% (t-statistics=6.29). In addition, we conduct a bivariate portfolio analysis and a Fama-Macbeth (1973) regression and find that the negative relationship between APL beta and subsequent stock returns is robust after controlling for various firm characteristics.

To distinguish our findings from previous literature, we rule out several alternative explanations for our results. First, we show that our results differ from the direct attention-grabbing effect of price limits. Second, we confirm that our results are not driven by stocks' sensitivity to market volatility. Third, we show that Chinese specific risk factors do not explain our results.

Finally, we conduct several robustness checks to further corroborate our main findings. First, we confirm that our findings exist for both upper and lower price limits, which distinguishes our results from the effect of one-sided extreme returns such as the lottery-like effect and the max effect (e.g., Boyer et al., 2010; Bali et al., 2011; Barberis et al., 2016; Nartea et al., 2017; An et al., 2020). Second, we show that the return predictability of APL beta is not sensitive to the construction period.

Our paper contributes to the literature in several ways. First, our paper extends the literature on price limits. Prior literature documents various side effects of price limits, such as exacerbating overreaction (e.g., Ma et al., 1989; Cai et al., 2022), increasing volatility (e.g., Kim, Rhee, 1997, 2001), delaying the arrival of informed traders (e.g., Chan et al., 2005), and inducing magnet effects (e.g., Cho et al., 2003; Hsieh et al., 2009).[7] Among this strand of the literature, our paper is mostly related to Seasholes and Wu (2007) and Chen et al. (2019), who investigate account level data in China and provide empirical evidence in which investors pay more attention to stocks that hit upper price limits. Our paper is complementary to theirs by showing that the attention-grabbing effect can spill over to stocks that are sensitive to price limits.

Second, our paper contributes to the literature on investors' attention allocation (e.g., Liu and McConnell, 2013; Huang et al., 2019). Related to this literature, we construct an empirical measure, APL beta, to capture the sensitivity of stocks to limit-hitting events, which captures investors' attention allocation to stocks that are sensitive to price limits.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 shows the main empirical findings. Section 4 rules out other alternative explanations. Section 5 provides more evidence for the attention-grabbing channel. Section 6 checks the robustness, and Section 7 concludes.

2. Data

2.1. Proportion of limits-hitters (LHs)

We obtain data for daily stock prices and returns from the China Stock Market and Accounting Research (CSMAR) Database. To eliminate the effect of the 2005 share-splitting reform in China, we start our sample in January 2006. Therefore, our sample covers the period from January 2006 to December 2020 and includes 4229 stocks and 8,593,023 daily return observations.[8]

The daily price limit is 10% for regular stocks in China. However, since the minimum tick size is ¥ 0.01, the actual daily limits for some stocks might be lower than 10%. For example, if the opening price for stock A is ¥ 1.19, the maximum daily closing price is ¥ 1.30 (the closing price cannot exceed ¥ 1.309), which means the maximum daily return is 9.24%. Therefore, in our main analysis, we choose 9% as the threshold to identify the stocks that hit daily price limits. The distribution plot of daily stock returns in China is shown in Fig. 1. The figure shows that 3.1% of the daily returns are above 9% or below −9%. Therefore, stocks in China's market frequently hit price limits.

To investigate the sensitivity of each stock to daily price limits, we follow Kelly and Jiang (2014) and construct a market-wide proportion of limits-hitters (LHs) for each day. Specifically, for each

[3] The Chinese version of the news be found at https://baijiahao.baidu.com/s?id=1666462213366682872&wfr=spider&for=pc.

[4] We use the absolute value of the beta because stocks with either the highest or lowest beta are most sensitive to daily price limits. Later in the paper, we separately test stocks with the positive and negative price limits betas, and the results are consistent.

[5] See, for example, https://xw.qq.com/cmsid/20200810A0HCYE00.

[6] Due to the strong short-selling constraint in China, the buying pressure for stocks that are preferred by investors are much larger than is that for stocks that are disliked by investors, especially for stocks that are not included in the Chinese Margin Trading and Short Selling (MTSS) program (i.e., Gu et al., 2018). Therefore, stocks that receive higher investor's attention are more likely to be overpriced. This pattern is consistent with the prior literature such as Chemmanur and Yan (2019).

[7] The magnet effect states that the tendency that stock prices accelerate to the upper price limits.

[8] Prior to 2005, a significant proportion of equity shares were nontradable. In April 2005, China initiated the share-splitting reform to convert the nontradable shares to tradable shares. The reform had tremendous impacts on the asset prices, corporate governance, and information disclosure strategy of Chinese enterprises (e.g., Firth et al., 2010; Li et al., 2011; Liao et al., 2014). To eliminate the influences of the share-splitting reform on our results, we start our sample period in January 2006. Nevertheless, our results are robust if we start our sample from 1992.

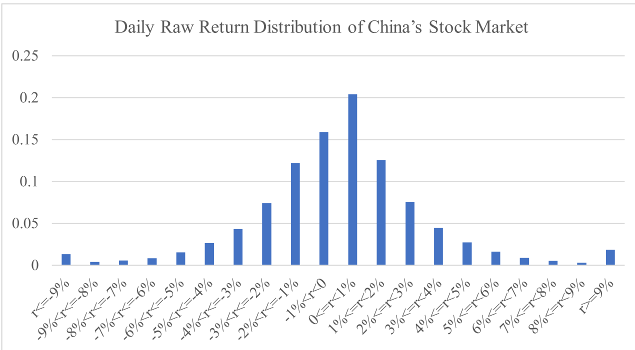

Fig. 1. Daily Raw Return Distribution of China's Stock Market.
Fig. 1 shows the distribution of daily returns in China's stock market. Our data is from China Stock Market and Accounting Research (CSMAR) Database, and our sample period is January 2006 to December 2020.

Table 1
Summary Statistics and Correlation Table.

Panel A: Summary Statistics					
	P1	Mean	Median	P99	Std
Return	−0.198	0.020	0.003	0.406	0.132
δ_d^{LH}	0.001	0.021	0.013	0.141	0.044
$\delta_{upper,\ d}^{LH}$	0.000	0.016	0.001	0.480	0.077
$\delta_{lower,d}^{LH}$	0.003	0.036	0.018	0.571	0.087
$\lvert\beta_{i,t}^{PL}\rvert$	0.008	0.609	0.428	2.858	0.991

Panel B: Correlation Table			
	$\delta_{upper,\ d}^{LH}$	$\delta_{lower,d}^{LH}$	δ_d^{LH}
$\delta_{upper,\ d}^{LH}$	1.00	−0.04	0.47
$\delta_{lower,d}^{LH}$	−0.04	1.00	0.86
δ_d^{LH}	0.47	0.86	1.00

Panel A provides the summary statistics of monthly returns, proportion of LHs and monthly APL beta. δ_d^{LH}, $\delta_{upper,\ d}^{LH}$ and $\delta_{lower,d}^{LH}$ represents the proportion of LHs on day d using full sample, only the upper price limits or only the lower price limits respectively. $|\beta_{i,t}^{PL}|$ represents APL beta. Panel B shows the correlation between δ_d^{LH}, $\delta_{upper,\ d}^{LH}$ and $\delta_{lower,d}^{LH}$. Our sample period is from January 2006 to December 2020.

trading day d, we calculate the proportion of LHs as follows:

$$\delta_d^{LH} = \frac{n_{upper,d} + n_{lower,d}}{N_d} * 100\%, \tag{1}$$

where δ_d^{LH} is the proportion of LHs on day d, N_d is the number of traded stocks on day d, $n_{upper,d}$ is the number of stocks whose returns are greater than or equal to 9% and $n_{lower,d}$ is the number of stocks whose returns are less than or equal to −9%. The summary statistics of δ_d^{LH} are shown in Table 1, Panel A.

One concern might be that the number of stocks that hit the upper (lower) price limits is mainly driven by market trends. For example, in bull (bear) markets, mechanistically more stocks will hit the upper (lower) price limits. To rule out this possibility, we construct $\delta_{upper,\ d}^{LH}$ and $\delta_{lower,\ d}^{LH}$ separately using only the daily returns that hit the upper or lower price limits and check their correlation. If the number of stocks that hit the upper (lower) price limits is mainly driven by economic trends, we should observe a significant and negative correlation between the variables. However, as shown in Table 1, Panel B, $\delta_{upper,\ d}^{LH}$ and $\delta_{lower,\ d}^{LH}$ are not correlated, with a correlation coefficient of −0.04. In Section 4.2, we conduct formal empirical tests to rule out the market volatility channel.

Another concern is that the proportion of LHs could be sensitive to the stock sample we selected to construct the concentration. For example, one concern might be that small stocks are more likely to be LHs. Therefore, any patterns we find could be driven by size (or other stock characteristics) rather than by sensitivity to daily price limits. To rule out this possibility, we divide the stocks into five groups based on common stock characteristics (e.g., one-month return, size, etc.) at the beginning of each month. We further calculate the proportion of LHs for each group and show the correlations in Table 2.

Table 2
Correlations of Limits-hitter Concentration among Subgroups.

Panel A: By return (one-month return)					
	P1	P2	P3	P4	P5
P1	1.00	0.98	0.96	0.95	0.91
P2	0.98	1.00	0.99	0.97	0.93
P3	0.96	0.99	1.00	0.99	0.94
P4	0.95	0.97	0.99	1.00	0.96
P5	0.91	0.93	0.94	0.96	1.00
Panel B: By size (total market value)					
	P1	P2	P3	P4	P5
P1	1.00	0.99	0.98	0.96	0.91
P2	0.99	1.00	0.99	0.98	0.93
P3	0.98	0.99	1.00	0.99	0.94
P4	0.96	0.98	0.99	1.00	0.96
P5	0.91	0.93	0.94	0.96	1.00
Panel C: By size (circulation market value)					
	P1	P2	P3	P4	P5
P1	1.00	0.97	0.96	0.95	0.89
P2	0.97	1.00	0.99	0.98	0.93
P3	0.96	0.99	1.00	0.99	0.94
P4	0.95	0.98	0.99	1.00	0.96
P5	0.89	0.93	0.94	0.96	1.00

This table reports time series correlation between monthly proportion of LHs estimated from the cross-section of stocks in each return quintile (Panel A), in each size quintile (Panel B and Panel C). Our sample period is from January 2006 to December 2020.

The correlations of the time series proportions of LHs for the return quintiles range from 0.89 to 0.99 in all three panels. Therefore, Table 2 confirms a high degree of commonality in the time-varying proportions of LHs across the firms, suggesting that our proportion of LHs is not sensitive to other stock characteristics. In Section 4.4, we formally rule out this possibility by conducting a series of bivariate portfolio analyses.

2.2. Absolute price limits (APL) beta

To determine which stocks are sensitive to daily price limits, in each month t, we estimate the price limits beta of individual stocks with the following regression:

$$r_{i,d} = \mu_{i,t} + \beta_{i,\ t}^{PL}\delta_d^{LH} + \rho_{1,i,t}Mkt_d + \rho_{2,i,t}SMB_d + \rho_{3,i,t}HML_d + \rho_{4,i,t}UMD_d + \varepsilon_{i,t}, \tag{2}$$

where δ_d^{LH} is the proportion of LHs on day d in month t; Mkt_d, SMB_d, HML_d are the Fama and French (1993) three factors returns on day d, UMD_d is the Carhart (1997) momentum factor returns on day d, and $\beta_{i,t}^{PL}$ is the price limits beta for stock i in month t. If $\beta_{i,t}^{PL}$ is far from zero and positive (negative) for stock i, the return of stock i is likely to be higher (lower) when more stocks hit price limits.

In Panel A of Fig. 2, we plot the proportion of stocks with extreme daily raw returns (|r|≥9%) in each price limits beta decile. The figure shows that stocks in both the top and bottom deciles are more likely to have extreme daily returns, which is consistent with our expectations that such stocks are more likely to be related to daily price limits.

Since a high absolute value of the price limits beta represents that the stock price is highly sensitive to the proportion of LHs, later, we use the absolute price limits (APL) beta to identify the

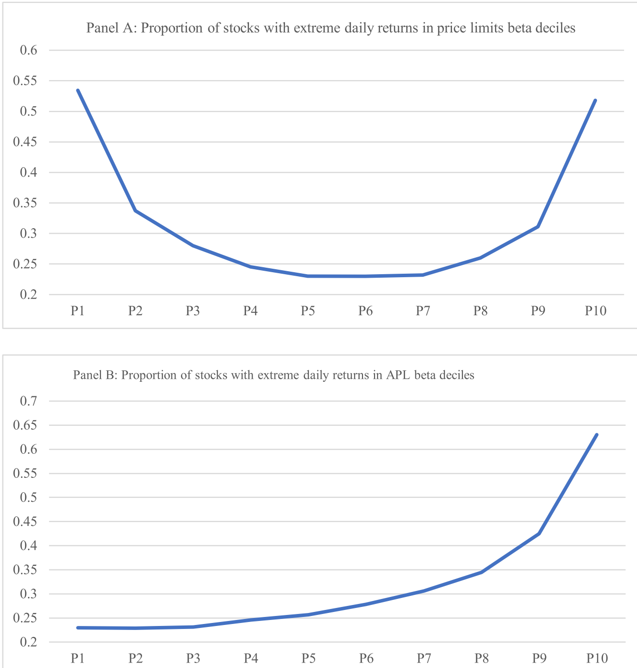

Fig. 2. Proportion of stocks with extremely daily raw return.
Panel A shows the proportion of stocks with extremely daily raw return ($|r|\geq 9\%$) in each price limits beta decile. Panel B shows the proportion of stocks with extremely daily raw return ($|r|\geq 9\%$) in each APL beta decile. Our sample period is from January 2006 to December 2020.

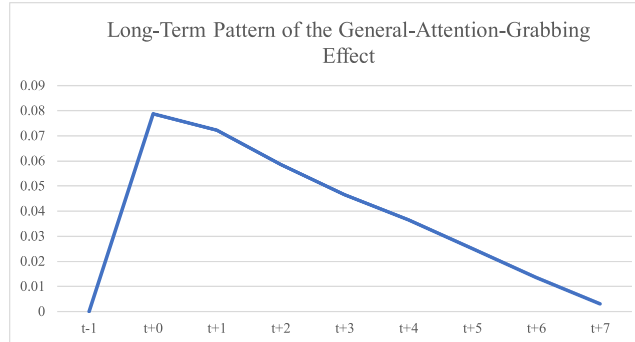

Fig. 3. Long-Term Pattern of the General-Attention-Grabbing Effect.
Fig. 3 shows the long-term pattern of the general-attention-grabbing effect. Stocks are sorted into decile portfolios based on APL beta at month t. This figure shows the cumulative differences of the Fama-French (2018) six-factor and Amihud (2002) illiquidity factor alphas between the top and bottom APL beta deciles. Our sample period is January 2006 to December 2020.

stocks that are more likely to be related to the daily price limits. To further validate the use of the absolute value, we plot the proportion of stocks with extreme daily raw returns ($|r|\geq 9\%$) in each APL beta decile in Panel B of Fig. 2. A clear ascending pattern in the figure supports our use of APL beta.

3. General-attention-grabbing effect

3.1. APL beta and investors' attention

In this subsection, we provide empirical evidence of the general-attention-grabbing effect of daily price limits. We first follow Barber and Odean (2008) and check the attention-grabbing measures for stocks with different levels of APL beta. We expect that high APL beta stocks attract more investors' attention and therefore have higher contemporaneous returns, higher buy-sell imbalances, higher turnover, and higher volumes.

In each month, we first estimate APL beta for each stock as in Eq. (2). Next, we divide the stocks into decile portfolios based on their APL beta. For each portfolio, we calculate the average contemporaneous returns, CAPM alphas, Fama-French (1996) three-factor alphas, Fama-French-Carhart (1997) four-factor alphas, turnover, trading volumes (natural logarithm), small order imbalances based on number of trades (NumSOIB), small order imbalances based on volume of trades (VolSOIB), and small order imbalances based on amounts of trades (AmoSOIB). Table 3 presents the results.

Two evident patterns are revealed in Table 3. First, returns and risk-adjusted returns increase with APL beta. For example, the difference in the returns (four-factor alphas) between the top and bottom deciles is 8.61% (7.80%), with t-statistics of 19.87 (14.39). Second, the portfolio with the highest APL beta has high average turnovers, trading volume, and small order imbalances. Both patterns are consistent with our hypothesis that stocks whose prices are more sensitive to daily price limits attract investors' attention.

3.2. APL beta and future stock returns

In this subsection, we investigate the asset pricing implications of the general-attention-grabbing effect of daily price limits. In the previous subsection, we show that investors are attracted by stocks that are sensitive to daily price limits. We conjecture that such stocks are overpriced in the short term and will reverse in later periods. To test our conjecture, we conduct a single portfolio sorting analysis and examine the one-month future returns of each portfolio. Specifically, we divide the stocks into decile portfolios based on their APL beta in month t. After the formation period, we compute the average one-month excess returns in month $t+1$ for each portfolio. Table 4 documents the results.

The table shows a significantly negative correlation between the average portfolio returns in month $t+1$ and the APL beta in month t. Specifically, the average return of the bottom APL beta decile is 2.04%, with a t-statistic of 2.34, while the average return of the top APL beta decile is only 0.89%, with a t-statistic of 0.99. The difference between the bottom and top deciles is -1.15%, with a t-statistic of -6.01. The differences are robust after controlling for common risk factors.[9]

Next, we check the longer-term return predictability of APL beta.[10] Due to the short-selling constraint in China, the overpricing caused by APL beta might not be able to be corrected in the short term, especially for stocks that are not included in China's Margin Trading and Short Selling (MTSS) program (i.e., Gu et al., 2018). Therefore, we expect to observe continual underpricing for stocks with a high APL beta. We document the cumulative Fama-French (2018) six-factor plus the Amihud (2002) illiquidity factor alphas in Fig. 3. The figure shows that on average, the overpricing caused by APL beta will be fully corrected in seven months.

4. Alternative explanations

In this subsection, we provide empirical evidence that is inconsistent with alternative explanations of the main findings that we documented in the previous section. Specifically, we rule out the explanations of the attention shocks caused by LHs, market volatility, China's specific risk factors, and other firm characteristics.

[9] We also calculate the value-weighted portfolio returns. The results are documented in Appendix Table A2, which are consistent with our main results.
[10] We thank an anonymous referee for this valuable suggestion.

Table 3
APL Beta and Attention-Grabbing Effect.

	RET	CAPM	FF3	Carhart4	Turnover	Volume	Numsoib	Volsoib	Amosoib
P1 (Low)	0.34%	−0.60%	−1.53%	−1.55%	0.492	20.798	0.005	−0.009	−0.009
P2	0.38%	−0.74%	−1.55%	−1.52%	0.494	20.809	0.004	−0.008	−0.009
P3	0.41%	−0.73%	−1.56%	−1.53%	0.501	20.809	0.005	−0.008	−0.008
P4	0.55%	−0.60%	−1.43%	−1.42%	0.511	20.830	0.005	−0.008	−0.008
P5	0.74%	−0.42%	−1.23%	−1.20%	0.528	20.841	0.005	−0.008	−0.008
P6	1.13%	−0.03%	−0.87%	−0.84%	0.557	20.880	0.005	−0.008	−0.007
P7	1.49%	0.31%	−0.55%	−0.55%	0.589	20.933	0.005	−0.007	−0.007
P8	2.28%	1.10%	0.22%	0.24%	0.638	21.007	0.004	−0.007	−0.007
P9	3.57%	2.29%	1.32%	1.34%	0.720	21.112	0.005	−0.005	−0.005
P10 (High)	8.61%	7.31%	6.22%	6.26%	0.976	21.313	0.007	−0.001	−0.002
P10-P1	8.26%***	7.90%***	7.75%***	7.80%***	0.484***	0.515***	0.003***	0.007***	0.007***
(t-stat)	(19.87)	(15.56)	(14.82)	(14.39)	(23.74)	(20.81)	(3.60)	(6.74)	(8.12)

This table reports contemporaneous average stock characteristics for portfolios formed based on APL beta. RET is monthly returns. CAPM is the CAPM alpha. FF3 is the Fama-French (1993) three-factor alphas. Carhart4 is the Fama-French-Carhart (1997) four-factor alphas. Turnover is the ratio of the number of shares traded in one month to by the total number of shares issued. Volume is the natural logarithm of the monthly trading volume. NumSOIB is small order imbalance based on number of trades, VolSOIB is small order imbalance based on volume of trades, AmoSOIB is small order imbalance based on amounts of trades. Each month stocks are sorted into decile portfolios based on APL beta that are estimated from daily data over the previous one month. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

Table 4
APL Beta and Future Stock Returns.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\lvert\beta_i^{PL}\rvert$	0.037	0.114	0.193	0.278	0.373	0.484	0.619	0.796	1.073	2.066	2.028
Raw Returns	2.04%**	2.11%**	2.03%**	1.97%**	1.82%**	1.75%**	1.75%**	1.58%*	1.47%*	0.89%	−1.15%***
	(2.34)	(2.43)	(2.28)	(2.23)	(2.11)	(2.03)	(2.04)	(1.82)	(1.73)	(0.99)	(−6.01)
CAPM Alphas	0.87%**	0.95%***	0.85%**	0.80%**	0.66%*	0.59%*	0.58%*	0.41%	0.30%	−0.30%	−1.18%***
	(2.54)	(2.81)	(2.39)	(2.26)	(1.90)	(1.71)	(1.66)	(1.16)	(0.85)	(−0.79)	(−6.34)
FF3 Alphas	0.03%	0.14%	0.00%	−0.04%	−0.18%	−0.24%**	−0.26%**	−0.44%***	−0.55%***	−1.14%***	−1.17%***
	(0.23)	(1.26)	(0.00)	(−0.32)	(−1.38)	(−1.98)	(−2.06)	(−3.29)	(−4.29)	(−6.94)	(−6.76)
Carhart4 Alphas	0.05%	0.22%**	0.06%	0.00%	−0.13%	−0.19%	−0.23%*	−0.45%***	−0.56%***	−1.19%***	−1.24%***
	(0.40)	(1.99)	(0.45)	(0.00)	(−0.97)	(−1.54)	(−1.88)	(−3.36)	(−4.34)	(−7.53)	(−7.84)
FF5 Alphas	0.12%	0.29%**	0.10%	0.01%	−0.12%	−0.18%	−0.20%	−0.37%***	−0.50%***	−1.02%***	−1.13%***
	(0.83)	(2.35)	(0.70)	(0.09)	(−0.85)	(−1.38)	(−1.61)	(−2.60)	(−4.04)	(−6.26)	(−6.61)
FF6 Alphas	0.12%	0.33%***	0.13%	0.03%	−0.09%	−0.15%	−0.19%	−0.38%***	−0.51%***	−1.05%***	−1.18%***
	(0.88)	(2.73)	(0.92)	(0.25)	(−0.64)	(−1.17)	(−1.55)	(−2.71)	(−4.11)	(−6.68)	(−7.28)
FF6+IML Alphas	0.12%	0.32%***	0.12%	0.02%	−0.08%	−0.15%	−0.17%	−0.36%***	−0.49%***	−1.02%***	−1.14%***
	(0.82)	(2.64)	(0.86)	(0.18)	(−0.62)	(−1.19)	(−1.46)	(−2.74)	(−3.91)	(−6.36)	(−6.29)

This table reports excess returns for portfolios formed based on APL beta. Each month stocks are sorted into decile portfolios based on APL beta that are estimated from daily data over the previous one month. We report the average absolute beta, excess return, and alphas using the CAPM model, the Fama-French three-factor model, the Carhart four-factor model, the Fama-French five-factor model, the Fama-French six-factor model as well as the Fama-French six-factor plus Amihud illiquidity factor model for each portfolio. The right-most column reports the differences between the top and bottom decile. Returns and alphas are expressed as percentage, with Newey-West (1987) adjusted t-statistics with four lags in brackets. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

4.1. Attention shocks of LHs

Prior literature has shown that stocks that hit daily price limits attract investors' attention shocks (e.g., Seasholes and Wu, 2007; Chen et al., 2019). To rule out the possibility that our results are driven by such attention shocks, we examine the relationship between APL beta and future stock returns for stocks that do not actually hit the price limits beta (called non-limits-hitters, or NLHs hereafter). Specifically, in each month, we first exclude all LHs and then sort the remaining stocks into decile portfolios according to their APL beta. We document the one-month future stock returns and risk-adjusted returns for each portfolio in Table 5 below.

Table 5 shows that APL beta still has strong cross-sectional return predictability for the NLHs. For example, the difference in the monthly returns (Fama-French six-factor plus Amihud illiquidity factor alphas) between the top and bottom portfolios is −0.63% (−0.72%), with a t-statistic of −3.23 (−4.79). Note that we only include stocks that did not hit price limits in the previous month, so such differences cannot possibly be driven by the direct attention-grabbing effect of daily price limits. Therefore, the results in Table 5 provide direct evidence of the spillover effect (general-attention-grabbing effect) of daily price limits.

4.2. Market volatility

Another concern is that our results are driven by market volatility. To see this, note that the proportion of stocks that hit daily price limits is mechanistically higher during periods with high market volatility. Therefore, the APL beta may simply measure stocks' sensitivity to market volatility. It is possible that investors' attention is unproportionally attracted by stocks that are more volatile during periods of high market volatility. Those stocks usually have higher concurrent returns and lower future returns. To rule out this possibility, we conduct three empirical tests in this section.

4.2.1. Absolute market volatility (AMV) beta

First, we investigate whether our results are driven by market volatility.[11] We construct the absolute market volatility (AMV) beta similar to Section 2.2. Specifically, on each day, we calculate the daily standard deviation of returns for all stocks trading in the market. Next, in each month t, we estimate the market volatility

[11] We thank Geert Bekaert, the managing director for this valuable suggestion.

Table 5
Future Stock Returns for NLHs.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\lvert\beta_i^{PL}\rvert$	0.037	0.114	0.193	0.278	0.373	0.484	0.619	0.795	1.068	1.711	1.674
Raw Returns	2.03%**	1.94%**	2.09%**	2.06%**	1.83%**	1.88%**	1.84%**	1.69%*	1.40%	1.41%	−0.63%***
	(2.29)	(2.22)	(2.25)	(2.26)	(2.07)	(2.15)	(2.08)	(1.93)	(1.52)	(1.50)	(−3.23)
CAPM Alphas	0.96%**	0.84%**	0.97%**	0.95%**	0.72%*	0.77%**	0.73%*	0.55%	0.23%	0.25%	−0.71%***
	(2.45)	(2.38)	(2.37)	(2.37)	(1.88)	(2.15)	(1.95)	(1.52)	(0.55)	(0.60)	(−3.67)
FF3 Alphas	0.14%	0.07%	0.16%	0.14%	−0.08%	−0.05%	−0.08%	−0.28%	−0.64%**	−0.56%**	−0.70%***
	(0.79)	(0.49)	(0.83)	(0.65)	(−0.46)	(−0.29)	(−0.45)	(−1.57)	(−2.00)	(−2.54)	(−4.19)
Carhart4 Alphas	0.18%	0.14%	0.23%	0.17%	−0.03%	−0.01%	−0.07%	−0.28%	−0.71%**	−0.61%***	−0.79%***
	(0.90)	(0.89)	(1.15)	(0.78)	(−0.16)	(−0.05)	(−0.40)	(−1.51)	(−2.11)	(−2.73)	(−5.32)
FF5 Alphas	0.32%	0.30%*	0.26%	0.26%	0.05%	0.00%	0.06%	−0.18%	−0.37%	−0.36%	−0.69%***
	(1.43)	(1.82)	(1.40)	(1.22)	(0.23)	(0.02)	(0.35)	(−0.87)	(−1.37)	(−1.64)	(−4.33)
FF6 Alphas	0.33%	0.32%**	0.30%	0.27%	0.07%	0.02%	0.05%	−0.19%	−0.44%	−0.41%*	−0.74%***
	(1.43)	(1.97)	(1.55)	(1.26)	(0.35)	(0.14)	(0.31)	(−0.88)	(−1.57)	(−1.85)	(−5.32)
FF6+IML Alphas	0.31%	0.29%*	0.27%	0.25%	0.07%	0.01%	0.04%	−0.21%	−0.48%*	−0.41%*	−0.72%***
	(1.25)	(1.82)	(1.41)	(1.08)	(0.31)	(0.04)	(0.21)	(−1.04)	(−1.75)	(−1.79)	(−4.79)

This table reports excess returns for NLHs in portfolios formed based on APL beta. Each month stocks are sorted into decile portfolios based on APL beta that are estimated from daily data over the previous one month. We report the average APL beta, excess return, and alphas using the CAPM model, the Fama-French three-factor model, the Carhart four-factor model, the Fama-French five-factor model, the Fama-French six-factor model as well as the Fama-French six-factor plus Amihud illiquidity factor model for each portfolio. The right-most column reports the differences between the top and bottom decile. Returns and alphas are expressed as percentage, with Newey-West (1987) adjusted *t*-statistics with four lags in brackets. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

beta of individual stocks with the following regression:

$$r_{i,d} = \mu_{i,t} + \beta_{i,\ t}^{MV} Std_d + \rho_{1,i,t} Mkt_d + \rho_{2,i,t} SMB_d + \rho_{3,i,t} HML_d + \rho_{4,i,t} UMD_d + \varepsilon_{i,t}, \tag{3}$$

where Std_d is the standard deviation of stock returns on day d in month t; Mkt_d, SMB_d, HML_d are the Fama and French (1993) three factors returns on day d, UMD_d is the Carhart (1997) momentum factor returns on day d, and $\beta_{i,t}^{MV}$ is the price limits beta for stock i in month t. We use the absolute value of $\beta_{i,t}^{MV}$ as the AMV beta.

Next, we conduct a 5 × 5 independent double portfolio sorting on the APL beta and AMV beta. We report the excess returns of each portfolio as well as the excess returns and Fama-French (2018) six-factor plus Amihud (2002) illiquidity factor alphas (seven-factor alphas) of long-short strategies in Panel A of Table 6. If the return predictability of APL beta merely comes from stocks' exposure to market volatility, we should observe that APL beta no longer predicts stock returns if we control for AMV beta. However, the results are inconsistent with this conjecture.

There are three interesting patterns in Panel A of Table 6. First, when AMV beta increases, the seven-factor alphas of the long-short strategies that long (short) low (high) APL beta stocks decrease, indicating that the return predictability of APL beta partially comes from stocks' exposure to market volatility. Second, even for the highest AMV beta quintile, the long-short strategies that long (short) low (high) APL beta stocks still generate economically and statistically significant seven-factor alphas, indicating that APL beta predicts stock returns even after controlling for stocks' exposure to market volatility. Third, in the highest APL beta quintile, the long-short strategies that long (short) low (high) AMV beta stocks no longer generate significant seven-factor alphas, suggesting that the exposure of price limits is a better return predictor than the exposure of market volatility.

4.2.2. Residual proportion of LHs

In this section, we use the residual proportion of LHs to alleviate the concern of the influences of market volatility. Specifically, in each month, we regress the daily proportion of LHs on the daily standard deviation of stock returns as follows:

$$\delta_d^{LH} = a_t + b_t Std_d + \delta_d^{RLH}, \tag{4}$$

where δ_d^{LH} is the proportion of LHs on day d in month t; Std_d is the standard deviation of stock returns on day d in month t. δ_d^{RLH} is the residual proportion of LHs we use for the next step.

As in the previous sections, we estimate the absolute residual price limits (ARPL) beta of individual stocks with the following regression:

$$r_{i,d} = \mu_{i,t} + \beta_{i,\ t}^{RPL} \delta_d^{RLH} + \rho_{1,i,t} Mkt_d + \rho_{2,i,t} SMB_d + \rho_{3,i,t} HML_d + \rho_{4,i,t} UMD_d + \varepsilon_{i,t}, \tag{5}$$

where δ_d^{RLH} is the residual proportion of LHs on day d in month t; Mkt_d, SMB_d, HML_d are the Fama and French (1993) three factors returns on day d, UMD_d is the Carhart (1997) momentum factor returns on day d, and $\beta_{i,t}^{RPL}$ is the residual price limits beta for stock i in month t.

Next, we conduct a single portfolio sorting analysis and examine the one-month future returns of each portfolio. Specifically, we divide the stocks into decile portfolios based on their ARPL beta in month t. After the formation period, we compute the average one-month excess returns in month $t+1$ for each portfolio and document the results in Panel B of Table 6.

The results clearly show that the ARPL beta predicts future stock returns. For example, the difference in the monthly returns (Fama-French six-factor plus Amihud illiquidity factor alphas) between the top and bottom portfolios is −1.11% (−1.13%), with a *t*-statistic of −5.90 (−6.55).

4.2.3. Placebo test: almost-hitters (AHs)

To further rule out the market volatility explanation, we conduct a placebo test in this subsection.[12] Specifically, we investigate whether the stocks that almost hit the daily price limits (called almost-hitters, or AHs hereafter) have the general-attention-grabbing effect. Specifically, we define stocks that have absolute daily returns greater than or equal to 8% but less than 9% as AHs. High market volatility increases the proportion of AHs, which is similar to LHs. Therefore, if our results are mainly driven by market volatility, we should also obtain the general-attention-grabbing effect from AHs.

To test the spillover effect of the AHs, we first construct the proportion of AHs and absolute almost-hitters (AAH hereafter) beta similar to the previous analysis. Specifically, on each trading day d, we calculate the daily almost-hitters concentration as follows:

$$\delta_d^{AH} = \frac{n_{upper,d}^{AH} + n_{lower,d}^{AH}}{N_d} * 100\%, \tag{6}$$

[12] We thank an anonymous associate editor for this valuable suggestion.

Table 6
Market Volatility and the General-Attention-Grabbing Effect.

Panel A: Double Portfolio Sorting on APL Beta and AMV Beta

		APL Beta								
		P1	P2	P3	P4	P5	P5-P1		FF6+IML Alphas	
AMV Beta	P1	2.17%	2.04%	1.93%	1.59%	1.15%	−1.00%***	(−4.21)	−1.20%***	(−5.19)
	P2	2.15%	2.01%	1.86%	2.05%	1.30%	−0.84%***	(−3.42)	−0.93%***	(−4.16)
	P3	2.19%	2.20%	1.82%	1.70%	1.24%	−0.95%***	(−4.02)	−1.08%***	(−4.26)
	P4	2.05%	1.98%	1.85%	1.66%	1.48%	−0.58%**	(−2.72)	−0.58%**	(−2.67)
	P5	1.48%	1.52%	1.34%	1.31%	0.90%	−0.57%***	(−3.62)	−0.42%**	(−2.92)
	P5-P1	−0.69%***	−0.52%**	−0.58%***	−0.28%**	−0.26%				
		(−3.24)	(−2.30)	(−3.45)	(−2.08)	(−1.31)				
	FF6+IML Alphas	−1.00%***	−0.71%***	−0.76%***	−0.33%***	−0.22%				
		(−5.24)	(−3.14)	(−4.31)	(−2.41)	(−1.12)				

Panel B: ARPL Beta and Future Stock Returns

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Raw Returns	1.99%	2.02%	1.90%	2.04%	1.91%	1.79%	1.82%	1.56%	1.52%	0.87%	−1.11%***
	(2.25)	(2.32)	(2.18)	(2.34)	(2.19)	(2.08)	(2.10)	(1.83)	(1.74)	(0.98)	(−5.90)
FF6+IML Alphas	0.10%	0.18%	0.02%	0.13%	0.01%	−0.13%	−0.15%	−0.36%	−0.45%	−1.03%	−1.13%***
	(0.68)	(1.41)	(0.13)	(0.99)	(0.07)	(−1.03)	(−1.24)	(−3.10)	(−3.33)	(−6.75)	(−6.55)

Panel C: Placebo Test-APL Beta based on AHs

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Raw Returns	1.98%**	2.04%**	1.95%**	1.88%**	2.01%**	1.89%**	1.68%*	1.63%*	1.44%	1.62%*	−0.40%
	(2.22)	(2.21)	(2.23)	(2.17)	(2.14)	(2.13)	(1.87)	(1.85)	(1.46)	(1.71)	(−1.30)
FF6+IML Alphas	0.26%	0.21%	0.14%	0.11%	0.24%	0.03%	−0.08%	−0.33%	−0.32%	−0.04%	−0.30%
	(1.10)	(1.06)	(0.75)	(0.63)	(1.02)	(0.18)	(−0.46)	(−1.63)	(−1.14)	(−0.08)	(−1.00)

This table examines the relationship between market volatility and the general-attention-grabbing effect. In Panel A, we report the results of independent double portfolio sorting. At the beginning of each month, all stocks are sorted into 5 × 5 portfolios based on APL beta and AMV beta of the previous month. We report excess returns for each portfolio and alphas using the Fama-French six-factor plus Amihud illiquidity factor model for the long-short strategy based on APL beta or AMV beta. In Panel B, we report the excess returns, and alphas using the Fama-French six-factor plus Amihud illiquidity factor model for each portfolio sorted on ARPL beta. In Panel C, we report the results of a placebo test. We calculate absolute AHs beta based on stocks with absolute daily returns exceed 8% but lower than 9%. For each portfolio, we report the excess returns and alphas using the Fama-French six-factor plus Amihud illiquidity factor model. Returns and alphas are expressed as percentage, with Newey-West (1987) adjusted *t*-statistics with four lags in brackets. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

where δ_d^{AH} is the proportion of AHs on day d, N_d is the number of trading stocks on day d, $n_{upper,d}^{AH}$ is the number of stocks whose returns are greater than or equal to 8% but less than 9%, and $n_{lower,d}^{AH}$ is the number of stocks whose returns are less than or equal to −8% but greater than −9%.

For each month, we estimate the AAH beta of the individual stocks with the following regression:

$$r_{i,d} = \mu_{i,t} + \beta_{i,\ t}^{AH}\delta_d^{AH} + \rho_{1,i,t}Mkt_d + \rho_{2,i,t}SMB_d + \rho_{3,i,t}HML_d + \rho_{4,i,t}UMD_d + \varepsilon_{i,t}, \tag{7}$$

where δ_d^{AH} is the proportion of AHs on day d in month t, Mkt_d, SMB_d, and HML_d are the Fama and French (1993) three-factor returns on day d, UMD_d is the Carhart (1997) momentum factor returns on day d, and $\beta_{i,t}^{AH}$ is the almost-hitters beta for stock i in month t.

Next, we exclude the stocks that hit or almost hit the daily price limits and sort all the other stocks into decile portfolios based on their AAH beta. The results are documented in Panel C of Table 6. As shown in the table, neither the raw returns nor the risk-adjusted returns are significantly different between the top and bottom deciles. The results indicate that the spillover effect does not exist for stocks with high volatility that do not hit the daily price limits.

4.3. Chinese risk factors

Liu et al. (2019) propose a Chinese four-factor model (CH4). They find that a revised version of the market, size, value, and turnover factors could explain most reported Chinese anomalies. To ensure that the general-attention-grabbing effect of the daily price limits is not driven by the Chinese-specific risk factors, we calculate the Chinese four-factor model (CH4) alphas for each portfolio.[13] Specifically, we follow Liu et al. (2019) and exclude 30% of the stocks with the lowest market values. Next, we calculate the APL beta for the remaining stocks as in Section 3. We sort the stocks into decile portfolios based on their APL beta, and we report the raw returns, Chinese three-factor alphas (CH3) and Chinese four-factor alphas (CH4) in Table 7.

Table 7 shows that the Chinese risk factors can partly explain the return predictability of APL beta. However, after controlling for the Chinese risk factors, APL beta still has statistically and economically significant cross-sectional return predictability. For example, the difference in the CH4 alphas between the top and bottom decile portfolios is −0.47% per month (with a *t*-statistic of −2.07), indicating that a long-short portfolio that buys (shorts) stocks from the lowest (highest) APL beta decile can generate a 5.64% CH4 alpha annually. Therefore, the general-attention-grabbing effect of daily price limits is not merely driven by the Chinese-specific factors identified in Liu et al. (2019).

4.4. Other firm characteristics

In this subsection, we investigate whether our empirical results are driven by firm-specific characteristics other than the general-attention-grabbing effect.[14] We use 5 × 5 independent sorts based on various firm-specific characteristics and APL beta. Portfolio 1 is the combined portfolio of the stocks with the lowest APL beta in

[13] We thank an anonymous referee for this valuable suggestion.

[14] The control variable definitions are shown in Appendix Table A1.

Table 7
Chinese Risk Factors and the General-Attention-Grabbing Effect.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
$\lvert\beta_i^{PL}\rvert$	0.0378	0.1142	0.1949	0.2820	0.3783	0.4896	0.6280	0.8102	1.0888	2.0135	1.9757
Raw Returns	1.68%**	1.81%**	1.60%*	1.50%*	1.56%*	1.56%*	1.54%*	1.43%*	1.30%	0.65%	−1.04%***
	(1.97)	(2.07)	(1.89)	(1.75)	(1.76)	(1.81)	(1.81)	(1.66)	(1.53)	(0.75)	(−5.46)
CH3 Alphas	0.21%***	0.27%**	0.13%	0.06%	0.09%	0.09%	0.23%***	0.11%	0.09%	−0.34%*	−0.54%***
	(2.66)	(2.47)	(1.40)	(0.55)	(1.20)	(1.07)	(2.77)	(1.16)	(0.74)	(−1.93)	(−2.64)
CH4 Alphas	0.22%**	0.28%**	0.13%	0.09%	0.12%	0.12%	0.27%***	0.15%	0.16%	−0.25%	−0.47%**
	(2.21)	(2.20)	(1.30)	(0.75)	(1.45)	(1.36)	(3.03)	(1.59)	(1.41)	(−1.43)	(−2.07)

This table reports excess returns in portfolios formed based on APL beta after controlling for Chinese stock risk factors in Liu et al. (2019). Following Liu et al. (2019), we first exclude stocks with bottom 30% market value. Next, in each month, we sort stocks into decile portfolios based on APL beta that are estimated from daily data over the previous one month. We report the average absolute beta, excess return, and alphas using three-factor and four-factor models in Liu et al. (2019) The right-most column reports the differences between the top and bottom decile. Returns and alphas are expressed as percentage, with Newey-West (1987) adjusted *t*-statistics with four lags in brackets. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

Table 8
Bivariate Portfolio Analysis.

	P1	P2	P3	P4	P5	P5-P1
RET	0.12%	0.02%	−0.13%	−0.26%**	−0.60%***	−0.71%***
	(0.97)	(0.15)	(−1.04)	(−2.14)	(−4.62)	(−6.43)
LRET	0.20%	0.04%	−0.09%	−0.23%*	−0.68%***	−0.87%***
	(1.49)	(0.34)	(−0.78)	(−1.94)	(−4.95)	(−6.20)
SIZE	0.20%	0.08%	−0.08%	−0.32%***	−0.73%***	−0.92%***
	(1.60)	(0.63)	(−0.61)	(−2.69)	(−5.37)	(−7.16)
PRICE	0.15%	0.06%	−0.11%	−0.25%**	−0.69%***	−0.84%***
	(1.19)	(0.44)	(−0.88)	(−2.04)	(−5.62)	(−6.77)
PE	0.20%	0.05%	−0.08%	−0.24%*	−0.63%***	−0.83%***
	(1.61)	(0.42)	(−0.69)	(−1.82)	(−4.68)	(−6.40)
BM	0.20%	0.09%	−0.13%	−0.22%*	−0.68%***	−0.88%***
	(1.62)	(0.69)	(−1.02)	(−1.88)	(−4.94)	(−6.40)
MOM	0.23%*	0.06%	−0.01%	−0.12%	−0.55%***	−0.78%***
	(1.84)	(0.52)	(−0.08)	(−0.92)	(−4.22)	(−5.85)
VOLUME	0.17%	−0.03%	−0.10%	−0.29%**	−0.60%***	−0.77%***
	(1.30)	(−0.22)	(−0.80)	(−2.45)	(−4.40)	(−5.37)
TURNOVER	0.09%	−0.05%	−0.15%	−0.24%**	−0.49%***	−0.58%***
	(0.69)	(−0.45)	(−1.22)	(−2.02)	(−3.72)	(−4.89)
MAX	0.07%	−0.05%	−0.11%	−0.25%**	−0.51%***	−0.58%***
	(0.60)	(−0.43)	(−0.93)	(−2.04)	(−4.00)	(−4.94)
IVOL	−0.01%	−0.08%	−0.17%	−0.14%	−0.39%***	−0.38%***
	(−0.06)	(−0.66)	(−1.46)	(−1.11)	(−3.13)	(−3.18)
GROWTH	0.19%	0.07%	−0.12%	−0.24%**	−0.76%***	−0.95%***
	(1.51)	(0.59)	(−0.93)	(−2.05)	(−5.70)	(−6.60)
ROE	0.20%	0.09%	−0.14%	−0.21%	−0.79%***	−0.99%***
	(1.61)	(0.75)	(−1.11)	(−1.62)	(−6.06)	(−7.08)
VOLATILITY	0.30%**	0.19%	−0.07%	−0.07%	−0.56%***	−0.86%***
	(2.47)	(1.48)	(−0.59)	(−0.60)	(−4.31)	(−6.54)
ILLIQUIDITY	0.19%	0.05%	−0.10%	−0.23%*	−0.76%***	−0.95%***
	(1.50)	(0.44)	(−0.81)	(−1.92)	(−5.40)	(−6.67)
AMOSOIB	0.19%	0.09%	−0.09%	−0.27%**	−0.74%***	−0.93%***
	(1.52)	(0.68)	(−0.73)	(−2.24)	(−5.59)	(−7.02)
NUMSOIB	0.20%	0.07%	−0.09%	−0.27%**	−0.74%***	−0.93%***
	(1.61)	(0.52)	(−0.73)	(−2.21)	(−5.63)	(−7.17)
VOLSOIB	0.19%	0.09%	−0.09%	−0.27%**	−0.74%***	−0.93%***
	(1.50)	(0.71)	(−0.72)	(−2.25)	(−5.61)	(−7.04)

This table presents results from the equal-weighted bivariate portfolios based on dependent double sorts of various firm-specific attributes and APL beta. First, quintile portfolios are formed every month based on a firm-specific attribute. Then, quintile portfolios are formed based on APL beta within each firm-specific attribute quintile. Portfolio 1 is the combined portfolio of stocks with the lowest APL beta in each firm-specific attribute quintile. Portfolio 5 is the combined portfolio of stocks with the highest APL beta in each firm-specific attribute quintile. This table reports one-month-ahead seven-factor alphas for equal-weighted portfolios. The last column in each panel shows the differences of monthly alphas between APL beta quintiles 5 and 1 for each firm-specific attribute. Alphas are calculated after adjusting for the market, size, value, momentum, profitability and investment factors of Fama-French (2018) six-factor and illiquidity factor of Amihud (2002). All variables are defined in detail in Appendix A. Alphas are presented in percentile. Newey-West (1987) adjusted *t*-statistics are presented in parentheses. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

each firm-specific characteristic quintile, whereas Portfolio 5 is the combined portfolio of the stocks with the highest APL beta in each firm-specific characteristic quintile. If return predictability is purely driven by other firm characteristics, we should observe an insignificant difference between the returns of Portfolios 1 and 5. We document the results in Table 8.

Table 8 presents the alphas of the Fama-French (2018) six-factor and Amihud (2002) illiquidity factor model. The findings suggest that, for all the control variables, the alphas exhibit an increasing pattern across the APL beta quintiles. For example, the first row shows that, when the one-month return is used as the con-

Table 9
Investor Attention and the General-Attention Grabbing Effect.

	P1	P2	P3	P4	P5	P5-P1
Panel A: By fund holding proportion						
C1	0.56%**	0.27%	−0.05%	−0.32%*	−0.74%***	−1.29%***
	(2.51)	(1.28)	(−0.25)	(−1.91)	(−4.00)	(−6.09)
C2	0.13%	0.21%	0.11%	−0.11%	−1.02%***	−1.15%***
	(0.69)	(1.23)	(0.58)	(−0.54)	(−5.80)	(−5.32)
C3	0.12%	0.08%	−0.22%	−0.39%**	−0.58%***	−0.70%***
	(0.71)	(0.52)	(−1.13)	(−2.14)	(−3.33)	(−3.81)
C4	0.01%	0.00%	−0.11%	−0.17%	−0.55%**	−0.56%***
	(0.05)	(0.01)	(−0.64)	(−0.99)	(−2.53)	(−2.88)
C5	−0.24%	−0.04%	−0.10%	−0.14%	−0.29%	−0.05%
	(−1.46)	(−0.26)	(−0.42)	(−0.70)	(−1.25)	(−0.23)
C5-C1						1.24%***
						(4.22)
Panel B: By trading volume						
C1	0.92%***	0.82%***	0.63%***	0.64%***	0.53%***	−0.39%***
	(5.00)	(5.57)	(4.16)	(5.19)	(3.23)	(−2.56)
C2	0.54%***	0.35%***	0.26%*	0.01%	−0.04%	−0.59%***
	(3.40)	(2.29)	(1.79)	(0.07)	(−0.29)	(−3.63)
C3	0.01%	−0.09%	−0.20%	−0.41%***	−0.73%***	−0.75%***
	(0.08)	(−0.56)	(−1.24)	(−2.60)	(−3.62)	(−3.83)
C4	−0.27%*	−0.47%***	−0.67%***	−0.59%***	−1.16%***	−0.89%***
	(−1.69)	(−3.23)	(−4.19)	(−3.49)	(−5.52)	(−3.70)
C5	−0.37%***	−0.75%***	−0.52%**	−1.09%***	−1.60%***	−1.23%***
	(−2.74)	(−4.49)	(−2.57)	(−6.38)	(−6.84)	(−5.34)
C5-C1						−0.84%***
						(−3.24)
Panel C: By Small Order Imbalance						
C1(Low)	0.53%***	0.52%***	0.44%***	0.43%***	0.23%	−0.29%*
	(2.79)	(2.84)	(2.68)	(2.32)	(1.39)	(−1.69)
C2	0.43%***	0.24%	0.04%	0.04%	−0.50%***	−0.93%***
	(2.67)	(1.61)	(0.25)	(0.28)	(−3.56)	(−5.72)
C3	0.18%	−0.04%	−0.16%	−0.71%***	−0.97%***	−1.16%***
	(1.17)	(−0.27)	(−0.94)	(−4.78)	(−5.89)	(−6.46)
C4	−0.03%	−0.25%	−0.52%***	−0.65%***	−1.35%***	−1.32%***
	(−0.20)	(−1.47)	(−3.45)	(−3.65)	(−8.23)	(−7.79)
C5(High)	−0.12%	−0.14%	−0.25%	−0.44%**	−1.09%***	−0.97%***
	(−0.74)	(−0.75)	(−1.30)	(−2.38)	(−4.67)	(−4.13)
C5-C1						−0.68%***
						(−2.63)

This table presents the results of bivariate portfolio analyses of the relation between one-month-ahead stock returns and APL beta after controlling for the investor attention measures. Portfolio 1 is the portfolio of stocks with the lowest APL beta and Portfolio 5 is the portfolio of stocks with the highest APL beta. Panel A (Panel B) (Panel C) presents the one-month-ahead equal-weighted seven-factor adjusted alphas to portfolios that are dependently sorted on fund holding proportion (trading volume) (small order imbalance based on trade number) into quintiles first and then on APL beta quintiles into quintiles within each control portfolios. The last four columns of each panel show the differences of monthly Fama-French (2018) six-factor and Amihud (2002) illiquidity factor alphas and corresponding *t*-statistics between APL beta quintiles 5 and 1 within each small order imbalance quintile. Returns and alphas are presented in percentile. Newey-West (1987) adjusted *t*-statistics are presented in parentheses. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

trol variable, Portfolio 1 has an alpha of 0.12% (with a *t*-statistic of 0.97), whereas Portfolio 5 has an alpha of −0.60% (with a *t*-statistic of −4.62). The difference in the alphas between the top and bottom APL beta quintiles is −0.71% with a *t*-statistic of −6.43. Similar results are observed for all other control variables. These results rule out the possibility that return predictability is driven purely by other firm characteristics.

We also conduct a Fama-MacBeth (1973) regression and document the results in Appendix Table A3. The results are consistent with Table 8. In summary, the empirical evidence confirms that the return predictability of APL beta is not driven by other firm characteristics.

5. Investors’ attention and the general-attention-grabbing effect

In the previous section, we argue that stocks sensitive to daily price limits attract more investor attention, which has two implications. First, it implies that the subsequent negative predictive power of APL beta is driven by buying pressures from retail investors. Therefore, we expect the predictive power of APL beta to be stronger among stocks that are heavily invested in by retail investors. Second, we expect the negative predictive power of APL beta to be stronger among stocks that experience higher concurrent returns. In this section, we provide empirical evidence to support two conjectures.

5.1. Unsophisticated investors’ attention

First, we check whether the predictive powers of APL beta are stronger for stocks that are more heavily invested in by retail investors. Since short-term overpricing and subsequent reversals are driven by investors’ attention, the effect of overpricing should be stronger among the stocks that attract more retail investors. Specifically, the effect of overpricing is more pronounced among stocks with lower institutional ownership, larger trading volume,

Table 10
Concurrent Stock Returns and Future Reversals.

	P1(Low)	P2	P3	P4	P5(High)	P5-P1
C1(Low)	0.45%**	0.56%***	0.32%	0.19%	0.00%	−0.44%**
	(2.11)	(2.59)	(1.54)	(0.87)	(0.02)	(−2.47)
C2	0.46%***	0.52%***	0.38%*	0.18%	−0.20%	−0.66%***
	(2.77)	(3.16)	(1.90)	(1.30)	(−1.05)	(−4.18)
C3	0.42%***	0.17%	0.13%	−0.07%	−0.20%	−0.62%***
	(2.65)	(1.09)	(0.86)	(−0.41)	(−1.28)	(−4.34)
C4	0.11%	−0.01%	−0.28%	−0.20%	−0.77%***	−0.88%***
	(0.64)	(−0.09)	(−1.52)	(−0.99)	(−4.24)	(−5.30)
C5(High)	−0.85%***	−1.14%***	−1.19%***	−1.39%***	−1.81%***	−0.96%***
	(−3.94)	(−5.20)	(−5.57)	(−6.21)	(−7.00)	(−3.91)
C5-C1						−0.52%**
						(−1.97)

This table presents the results of bivariate portfolio analyses of the relation between concurrent stock returns and the return predictive power of APL beta. Portfolio P1 is the portfolio of stocks with the lowest APL and Portfolio P5 is the portfolio of stocks with the highest APL beta. We document the equal-weighted seven-factor adjusted alphas to portfolios that are dependently sorted on concurrent returns into quintiles first and then on APL beta quintiles into quintiles within each control portfolios. The last column of each panel shows the differences of monthly Fama-French (2018) six-factor and Amihud (2002) illiquidity factor alphas and corresponding *t*-statistics between APL beta quintiles 5 and 1 within each control portfolios. Alphas are presented in percentile. Newey-West (1987) adjusted *t*-statistics are presented in parentheses. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

and higher small order imbalance (e.g., Barber and Odean, 2008; Huang et al., 2016). Empirically, we conduct a dependent double sorting analysis and present the results in Table 9.

We first sort the stocks by their fund-holding proportion (Panel A), trading volume (Panel B), and small order imbalance (Panel C). We report the difference in the alphas from the Fama-French (2018) six-factor and Amihud (2002) illiquidity factor model (seven-factor model). Consistent with our conjecture, the negative relationship between APL beta and future returns is stronger among stocks heavily invested in by retail investors (i.e., stocks with low fund holding proportions, high trading volumes and high small order imbalances).

Moreover, Panel A of Table 9 shows that the relationship between APL beta and future stock returns is significant only among stocks with medium or low institutional ownership, which are more sensitive to retail investors' attention. For example, the difference in the seven-factor alphas between the top and bottom APL beta quintiles is −1.29% per month (with a *t*-statistic of −6.09) for stocks with institutional ownership in the bottom 20%. In contrast, the difference in the seven-factor alphas between the top and bottom APL beta quintiles is −0.05% per month (with a *t*-statistic of −0.23) for stocks with institutional ownership in the top 20%. From the bottom to the top institutional ownership quintiles, the difference in the seven-factor alphas across APL beta portfolios increases by 1.24% (with a *t*-statistic of 4.22), indicating that the return predictability of APL beta is much stronger for firms with lower institutional ownership.

Panels B and C of Table 9 show similar patterns. From the bottom to the top of the trading volume (small order imbalance) quintiles, the difference in the seven-factor alphas across APL beta portfolios decreases by 0.84% (0.68%). Therefore, the return predictability of the APL beta is much stronger for firms with higher trading volumes and higher small order imbalances.

5.2. Concurrent stock returns and future reversals

Next, we check the relationship between concurrent returns and the predictive power of APL beta. If the return predictability of APL beta is driven by investors' attention, the return predictability will be stronger for stocks with high concurrent returns. We conduct double portfolio sorting by sorting stocks first on the concurrent returns and then on the APL beta. We document the next month's alphas of the Fama-French (2018) six-factor and Amihud (2002) illiquidity factor model (seven-factor alphas) for each portfolio in Table 10, which shows that the negative relationship between APL beta and future stock returns is much stronger for stocks with high concurrent returns. For example, the difference in the seven-factor alphas between the top and bottom APL beta quintiles is -0.44% per month for stocks with the bottom 20% concurrent returns. In contrast, the difference in the seven-factor alphas between the top and bottom APL beta quintiles is −0.96% per month for stocks with the top 20% concurrent returns. The difference of the seven-factor alphas is −0.52% (with a *t*-statistic of −1.97) between the top and bottom concurrent return quintiles.

6. Robustness checks

6.1. Positive and negative price limits betas

In the previous analysis, we mainly focus on the absolute value of the price limits beta. One concern is that our results might be driven purely by either the positive or negative price limits beta. If so, our results could be driven by tail risk (if only the negative price limits beta predicts future stock returns) or the investors' favoring of lottery stocks (if only the positive price limits beta predicts future stock returns). To rule out these possibilities, we separately investigate the return predictability of the upper and lower APL beta.

Specifically, on each trading day d, we calculate the daily proportion of upper- and lower-hitters as follows:

$$\delta_d^U = \frac{n_{upper,d}}{N_d} * 100\%, \tag{8}$$

$$\delta_d^L = \frac{n_{lower,d}}{N_d} * 100\%, \tag{9}$$

where δ_d^U (δ_d^L) is the proportion of upper-hitters (lower-hitters) on day d, N_d is the number of trading stocks on day d, $n_{upper,d}$ is the number of stocks whose returns are greater than 9%, and $n_{lower,d}$ is the number of stocks whose returns are less than −9%.

Next, in each month, we estimate the upper (lower) price limits beta of individual stocks with the following regression:

$$r_{i,d} = \mu_{i,t} + \beta_{i,\ t}^U \delta_d^U + \rho_{1,i,t}^U Mkt_d + \rho_{2,i,t}^U SMB_d + \rho_{3,i,t}^U HML_d + \rho_{4,i,t}^U UMD_d + \varepsilon_{i,t}, \tag{10}$$

$$r_{i,d} = \mu_{i,t} + \beta_{i,\ t}^L \delta_d^L + \rho_{1,i,t}^L Mkt_d + \rho_{2,i,t}^L SMB_d + \rho_{3,i,t}^L HML_d + \rho_{4,i,t}^L UMD_d + \varepsilon_{i,t}, \tag{11}$$

Table 11
Upper and Lower APL Beta.

	Upper APL Beta	Lower APL Beta
Raw Returns	−0.95%***	−1.09%***
	(−5.71)	(−6.33)
CAPM Alphas	−0.98%***	−1.13%***
	(−6.13)	(−6.67)
FF3 Alphas	−0.96%***	−1.16%***
	(−5.89)	(−7.34)
Carhart4 Alphas	−1.07%***	−1.22%***
	(−7.32)	(−8.27)
FF5 Alphas	−0.99%***	−1.12%***
	(−6.17)	(−7.53)
FF6 Alphas	−1.06%***	−1.16%***
	(−6.63)	(−8.19)
FF6+IML Alphas	−1.01%***	−1.13%***
	(−6.14)	(−7.19)

This table reports excess returns for portfolios formed based on upper and lower APL beta. Each month stocks are sorted into decile portfolios based on upper or lower APL beta that are estimated from daily data over the previous one month. We report excess return, and alphas using the CAPM model, the Fama-French three-factor model, the Carhart four-factor model, the Fama-French five-factor model, the Fama-French six-factor model as well as the Fama-French six-factor plus Amihud illiquidity factor model for the differences between the top and bottom deciles. Returns and alphas are expressed as percentage, with Newey-West (1987) adjusted *t*-statistics with four lags in brackets. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

Table 12
Alternative APL Beta and Future Stock Returns.

	3 Months	6 Months	1 Year	3 Years
Raw Returns	−0.84%***	−0.53%***	−0.43%***	−0.33%*
	(−4.65)	(−2.92)	(−2.67)	(−1.85)
CAPM Alphas	−0.87%***	−0.51%***	−0.45%***	−0.46%***
	(−4.87)	(−2.91)	(−2.87)	(−2.99)
FF3 Alphas	−0.95%***	−0.59%***	−0.55%***	−0.51%***
	(−5.58)	(−3.98)	(−3.87)	(−3.53)
Carhart4 Alphas	−1.07%***	−0.70%***	−0.66%***	−0.58%***
	(−7.00)	(−4.92)	(−4.69)	(−3.98)
FF5 Alphas	−1.11%***	−0.78%***	−0.75%***	−0.50%***
	(−6.19)	(−5.21)	(−4.92)	(−3.16)
FF6 Alphas	−1.18%***	−0.84%***	−0.81%***	−0.54%***
	(−7.15)	(−5.98)	(−5.50)	(−3.47)
FF6+IML Alphas	−1.16%***	−0.82%***	−0.82%***	−0.53%***
	(−6.30)	(−5.37)	(−5.43)	(−3.40)

This table reports excess returns for portfolios formed based on alternative APL beta. Specifically, each month stocks are sorted into decile portfolios based on APL beta that are estimated from daily data over the previous 3 months, 6 months, one year and monthly data over the previous three years, respectively. We report the differences between the top and bottom decile of the excess returns, and alphas using the CAPM model, the Fama-French three-factor model, the Carhart four-factor model, the Fama-French five-factor model, the Fama-French six-factor model as well as the Fama-French six-factor plus Amihud illiquidity factor model for each portfolio. Returns and alphas are expressed as percentage, with Newey-West (1987) adjusted *t*-statistics with four lags in brackets. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

where Mkt_d, SMB_d, and HML_d are the Fama and French (1993) three-factor returns on day d in month t, UMD_d is the Carhart (1997) momentum factor returns on day d, and $\beta^U_{i,t}$ ($\beta^L_{i,t}$) is the upper (lower) price limits beta for stock i in month t.

Finally, in each month, we sort the stocks into decile portfolios based on the absolute value of the upper (lower) price limits beta. We calculate the excess returns and alphas of various factor models for a long-short portfolio that buys stocks in the top absolute upper (lower) price limits beta portfolio and sells stocks in the bottom absolute upper (lower) price limits beta portfolio. We document the results in Table 11.

The results show that both the absolute upper and lower price limits betas have statistically and economically significant cross-sectional return predictive power. Therefore, our results are unlikely to be driven purely by tail risk or investors' favoring of lottery stocks.

6.2. Long-term APL beta

In this subsection, we show that our results are not sensitive to the methodology used to calculate APL beta. Specifically, in each month, we use a 3-month to 3-year sample to estimate the price limits beta for each stock. In Table 12, we document the excess returns and alphas of the various factor models for a long-short portfolio that buys (sells) stocks in the top (bottom) APL beta portfolio.

The results show that the general-attention-grabbing effect is not sensitive to the sample periods when we calculate APL beta. Therefore, the results indicate that the sensitivity of stocks to their peers who hit the daily price limits could be driven by some long-term economic relationships.

7. Conclusion

In this paper, we provide empirical evidence that investors are attracted to stocks that not only hit the upper daily price limits but that are also sensitive to the daily price limits. We choose the largest stock market with daily price limits, China's stock market, as our testing venue and find that stocks that are more sensitive to daily price limits attract investors' attention and are overpriced in the short term. We construct a general-attention-grabbing measure, the APL beta, and find that stocks with higher APL beta have higher contemporaneous but lower future returns.

We provide empirical evidence that rules out other alternative explanations of the return predictability driven by the APL beta, including the direct attention-grabbing effect of daily price limits, market volatility, Chinese risk factors, and other common firm characteristics. We show that the return predictability of the APL beta is stronger for stocks that are heavily invested in by retail investors. We also find that our results are not driven purely by stocks with positive or negative price limits betas.

CRediT authorship contribution statement

Fengjiao LIN: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Zhigang QIU:** Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Weinan ZHENG:** Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix

Table A1, Table A2, Table A3

Table A1
Variable Definitions.

Variable	Definition
RET	The monthly return of stock *i* in month *t*.
SIZE	Firm size at each month *t*, measured using the natural logarithm of the market value of equity at the end of month *t*.
PRICE	The price of stock *i* at the end of month *t*.
PE	The price-to-earnings ratio.
BM	The book-to-market ratio.
MOM	The momentum effect of each stock in month *t*, measured by the cumulative return over the previous 11 months with 2 months skipped (i.e., the cumulative return from month *t*-12 to month *t*-2).
LRET	The lagged monthly return for each stock in month *t*-1.
VOLUME	The monthly trading volume.
TURNOVER	The turnover (in percentage points), calculated as the monthly trading volume divided by the outstanding month-end shares.
ROE	The return-to-equity ratio.
GROWTH	The total assets growth rate.
NUMSOIB	The small order imbalance based on the trade number.
VOLSOIB	The small order imbalance based on the trade volume.
AMOSOIB	The small order imbalance based on the trade amount.
ILLIQUIDITY	The illiquidity measure of Amihud (2002), calculated as the ratio of the absolute price change to the dollar trading volume for each stock on each day.
IVOL	The idiosyncratic volatility defined as the standard deviation of daily idiosyncratic returns. To calculate return residuals, we adjust for Fama and French (1993) three factors.
MAX	The maximum daily return of stock *i* in month *t*, defines as the highest daily returns of each stock in each month.
VOLATILITY	The volatility of stock *i* in month *t*, defined as the standard deviation of daily returns during month *t*-11 to month *t*.

In this table, we provide detailed definitions of the control variables used in the article.

Table A2
APL Beta and Future Stock Returns: Value-Weighted.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Raw Returns	1.37%*	1.49%*	1.40%*	1.24%	1.32%	1.18%	1.24%	1.21%	1.11%	0.80%	−0.57%*
	(1.81)	(1.91)	(1.78)	(1.58)	(1.44)	(1.46)	(1.48)	(1.44)	(1.36)	(0.92)	(−1.64)
CAPM Alphas	0.28%**	0.42%**	0.29%*	0.14%	0.13%	0.08%	0.06%	0.03%	−0.10%	−0.45%	−0.73%**
	(1.98)	(2.53)	(1.87)	(0.79)	(0.63)	(0.38)	(0.31)	(0.16)	(−0.44)	(−1.49)	(−2.11)
FF3 Alphas	0.17%	0.29%*	0.10%	−0.02%	−0.01%	−0.09%	−0.25%	−0.20%	−0.34%	−0.78%***	−0.94%***
	(1.11)	(1.88)	(0.69)	(−0.13)	(−0.03)	(−0.48)	(−1.44)	(−1.05)	(−1.58)	(−3.23)	(−2.91)
Carhart4 Alphas	0.17%	0.38%***	0.13%	0.03%	0.07%	−0.03%	−0.29%*	−0.23%	−0.37%*	−0.89%***	−1.06%***
	(1.15)	(2.58)	(0.96)	(0.18)	(0.36)	(−0.13)	(−1.77)	(−1.24)	(−1.78)	(−4.02)	(−3.60)
FF5 Alphas	0.10%	0.49%***	0.23%	−0.09%	0.05%	−0.08%	−0.30%*	−0.13%	−0.29%	−0.66%***	−0.76%***
	(0.67)	(2.99)	(1.50)	(−0.49)	(0.21)	(−0.37)	(−1.80)	(−0.65)	(−1.48)	(−2.94)	(−2.58)
FF6 Alphas	0.11%	0.54%***	0.24%	−0.05%	0.10%	−0.03%	−0.33%**	−0.16%	−0.32%	−0.74%***	−0.85%***
	(0.73)	(3.35)	(1.59)	(−0.27)	(0.45)	(−0.16)	(−2.00)	(−0.79)	(−1.63)	(−3.56)	(−3.18)
FF6+IML Alphas	0.10%	0.52%***	0.25%*	−0.03%	0.09%	−0.03%	−0.31%**	−0.10%	−0.26%	−0.66%***	−0.76%***
	(0.66)	(3.21)	(1.66)	(−0.18)	(0.43)	(−0.14)	(−2.00)	(−0.55)	(−1.32)	(−3.08)	(−2.61)

This table reports value-weighted returns for portfolios formed based on APL beta. Each month stocks are sorted into decile portfolios based on APL beta that are estimated from daily data over the previous one month. We report the excess returns, and alphas using the CAPM model, the Fama-French three-factor model, the Carhart four-factor model, the Fama-French five-factor model, the Fama-French six-factor model as well as the Fama-French six-factor plus Amihud illiquidity factor model for each portfolio. The right-most column reports the differences between the top and bottom decile. Returns and alphas are expressed as percentage, with Newey-West (1987) adjusted *t*-statistics with four lags in brackets. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

Table A3
Fama-MacBeth Regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\lvert\beta^{PL}\rvert$	−0.016***	−0.027***	−0.016*	−0.014*	−0.013*	−0.013*	−0.013*
	(−2.64)	(−2.87)	(−1.88)	(−1.80)	(−1.75)	(−1.79)	(−1.81)
$RET_{i,\ t-1}$		−0.007	0.006	0.008	0.007	0.008	0.008
		(−1.20)	(1.01)	(1.34)	(1.35)	(1.45)	(1.39)
SIZE		−0.003**	−0.006***	−0.005***	−0.005***	−0.006***	−0.006***
		(−2.25)	(−3.89)	(−3.68)	(−3.89)	(−3.97)	(−4.15)
BM		0.003	0.004	0.005	0.005	0.003	0.004
		(0.55)	(0.78)	(0.94)	(1.15)	(0.89)	(1.04)
PE		0.000	0.000	0.000	0.000	0.000	0.000
		(−0.34)	(−0.60)	(−0.79)	(−0.97)	(−1.00)	(−0.20)
MOM			−0.002	−0.001	−0.001	−0.001	−0.002
			(−0.43)	(−0.16)	(−0.29)	(−0.37)	(−0.54)
Max			−0.061***	−0.028	−0.033	−0.033	−0.036
			(−2.91)	(−0.85)	(−0.99)	(−1.01)	(−1.10)
VOLATILITY			0.008	0.004	0.004	0.002	0.003
			(0.75)	(0.37)	(0.35)	(0.22)	(0.29)
ILLIQUIDITY			3.539*	4.207**	3.878*	3.950*	4.132**
			(1.77)	(2.03)	(1.87)	(1.92)	(2.10)
TURNOVER			−0.019***	−0.020***	−0.020***	−0.020***	−0.020***
			(−7.82)	(−7.75)	(−7.89)	(−7.87)	(−7.83)
IVOL				−0.145	−0.136)	−0.138	−0.111
				(−1.33)	(−1.24)	(−1.26)	(−1.03)
PRICE					0.000	0.000	0.000
					(0.24)	(0.15)	(−0.23)
GROWTH						0.009***	0.008***
						(4.45)	(3.99)
ROE							0.047***
							(3.41)
Intercept	0.019**	0.069***	0.107***	0.102***	0.105***	0.107***	0.109***
	(2.20)	(2.62)	(4.21)	(4.01)	(4.18)	(4.26)	(4.23)
Adj.R^2	0.53%	5.81%	8.84%	8.93%	9.48%	9.53%	9.87%

This table presents results from the Fama-MacBeth regressions of future equity returns on APL beta ($\lvert\beta^{PL}\rvert$) and various control variables. Reported coefficients are time-series averages from monthly Fama-MacBeth (1973) regressions and the associated *t*-statistics are reported using the Newey-West (1987) procedure. Average R-squared statistics for each regression are presented in the last row. Firm-specific characteristics are defined in Appendix Table A1. Our sample period is from January 2006 to December 2020. *, **, and *** indicate significance level at 10%, 5%, and 1%, respectively.

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