Price Limits and the Value Premium in the Taiwan Stock Market☆

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Abstract

By proposing a measure of limit-hit frequency, this paper provides the first investigation to understand whether and how price limits are related to the cross-section of stock returns. Based on a sample of listed stocks in Taiwan, we show that the value premium is stronger among stocks with lower limit-hit frequency. This evidence is consistent with the prediction of the limited-attention explanation and rejects the limits-to-arbitrage hypothesis for the value premium in Taiwan. Further analyses indicate that the association between limit-hit frequency and the value premium is robust to several alternative explanations.

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1. Introduction

As one of the major circuit breaker mechanisms adopted in financial markets worldwide, the price limit is imposed to prevent asset prices from excessive fluctuation. Previous studies mostly focus on the pros and cons of price limits and the price behavior surrounding limit hits (e.g., Kim and Rhee, 1997; Cho, Russell, Tiao, and Tsay, 2003; Kim, Yagüe, and Yang, 2004; Kim and Yang, 2004, 2008; Chan, Kim, and Rhee, 2005). However, how do price limits affect stock prices and whether price limits are related to asset-pricing anomalies still remain unclear to the literature. The objective of this study is to provide the first investigation to fill up this gap.

Motivated by Kim and Limpaphayom's (2000) empirical finding that stocks with higher degrees of behavioral characteristics (higher volatility, higher turnover, and smaller size) hit limit prices more often than other stocks, we propose a measure of limit-hit frequency which represents the dual role in capturing different behavioral biases and examine its impacts on the cross-sectional variations of stock returns. Specifically, for every month we define limit-hit frequency as the number of days that a stock's closing price hits its up- or down-limit prices over the previous 12 months divided by the number of trading days during the same period. We hypothesize that the measure is associated with the degrees of limits-to-arbitrage and investor attention.

On the one hand, price limits represent a form of arbitrage risk that impedes arbitrageurs from engaging in arbitrage activities to correct for potential mispricing (Chou, Chou, Ko, and Chao, 2013). If stocks hit their limit prices more often due to investors' overreaction, arbitraging in these stocks may be more risky and costly, thus refraining arbitrageurs to exploit the profitable opportunities embedded in the mispricing. On the other hand, limit-hit frequency is also positively correlated with investor attention because Seasholes and Wu (2007) indicate that price limit events serve as a natural experiment of attention-grabbing events. They find that up price limit events display three characteristics associated with attention-grabbing events as in Barber and Odean (2008), including high returns, high volume, and news coverage. When stocks hit their up-limit prices, the event catches individual investors' attention and further induce them to buy those stocks they have not previously owned.

But what is the channel through which limit-hit frequency relates to the cross-section of stock returns? The hypothesis of limits-to-arbitrage and the limited-attention theory have different predictions on the relation between limit-hit frequency and the return patterns of asset-pricing anomalies. The former suggests that when a stock is mispriced, arbitrageurs will engage in correcting such profit opportunities. Due to the fact that arbitrage is risky and costly in reality, implementable arbitrage opportunities are limited, especially when limits-to-arbitrage is severer. If asset-pricing anomalies are caused by mispricing, they are more difficult to be eliminated when risks and costs of arbitrage activities are higher. As a result, the hypothesis of limits-to-arbitrage predicts higher premia of asset-pricing anomalies among stocks with higher limit-hit frequency.

The hypothesis of limited-attention, however, proposes that when investors pay less attention to a stock, they are more likely to ignore or underreact to the stock's information or news, and therefore are unable to instantaneously adjust prices to fundamental values.

If asset-pricing anomalies are induced because of investors' underreaction to information, the return premia of asset-pricing anomalies should be more pronounced among stocks that receive less investor attention. That is, the limited-attention theory suggests that premia of asset-pricing anomalies are negatively correlated with limit-hit frequency.

Taking the two arguments together, we empirically examine the relation between limit-hit frequency and the cross-sectional variations of stock returns in the Taiwan Stock Exchange (TWSE). During our sample period from July 1982 to December 2015, limit hits are triggered more often in TWSE because of a narrower price-limit rule of not more than $+/-7\%$ than those imposed in most of the markets around the world. Hence the Taiwan stock market serves as a natural experimental environment to examine the two alternative hypotheses that are associated with price limits.[1]

Unlike the U.S. and most developed markets, the Taiwan stock market has been extensively demonstrated to exhibit no premium for the book-to-market (BM) effect (Chen and Zhang, 1998; Chui and Wei, 1998; Ding, Chua, and Fetherston, 2005). We first apply the Fama-MacBeth (1973) cross-sectional regressions to show that the earnings-to-price (EP) ratio is the only useful value strategy, while BM and the gross profitability (GP) of Novy-Marx (2013) fail to generate significant value premia in Taiwan. When limit-hit frequency is taken into account, we find that the positive relation between EP and stock returns is significantly stronger among stocks that hit their limit prices less frequently. This phenomenon

[1] Chung and Gan (2005) survey the price limit rules of 45 stock exchanges around the world and find that 26 out of them impose price limits. Among the 26 exchanges, only 6 of them have a price limit rule of not more than $+/-7\%$, including Wiener Borse AG (Austria), Prague (Czech Republic), Luxembourg, Mauritius, Taiwan, and Istanbul (Turkey). We introduce the detailed history of price limit rules in Taiwan in Section 3.1.

also holds true for the portfolio-based analyses. Specifically, the EP premium constructed using equal weights is significant at 0.648% per month among stocks with low limit-hit frequency and is insignificant at −0.402% per month among stocks with high limit-hit frequency. This pattern is robust to value weights and the Fama-French (1993) risk adjustments. Thus, our evidence is consistent with the prediction of the limited-attention theory rather than the limits-to-arbitrage argument in explaining the value premium in Taiwan.

To ensure that our evidence supports the limited-attention hypothesis in explaining the value premium, it is important to establish the direct linkage between limit-hit frequency and investors' attention. Using Barber and Odean's (2008) abnormal trading volume as a proxy for investor attention, we show that a firm's abnormal trading volume increases sharply around price limit events. Moreover, we show that during the formation period of limit-hit frequency, stocks that hit their limit prices more often also have higher abnormal volumes and thus capture investors' attention. Stocks with lower limit-hit frequency, however, have lower abnormal volumes and thus are subject to the limited attention from investors. This evidence provides a direct linkage between limit-hit frequency and investor attention and thus supports our finding that limited-attention theory is the main reason to underly the value premium in Taiwan.

In addition to discriminating cross-sectional return differences between high and low EP stocks, limit-hit frequency also captures market-wide attentiveness. By constructing an aggregate limit-hit frequency measure to capture investors' attentiveness to the overall stock market, we show that the EP strategy is profitable only in low attention periods but not in high attention periods. This finding indicates the credibility of the market-wide limit-hit frequency in explaining the time-varying patterns of the value premium and strengthens our support for the limited-attention theory in capturing the value premium in Taiwan.

Although our results are consistent with the limited-attention explanation for the value premium, we cannot rule out the possibility that the information content embedded in limit-hit frequency is related to other explanations or theories. Indeed, we find that limit-hit frequency is positively correlated with idiosyncratic volatility and turnover, but unrelated to illiquidity, firm age, and skewness. This confirms our conjecture that higher value of limit-hit frequency reflects higher degrees of limits-to-arbitrage and investor attention. Moreover, limit-hit frequency is unrelated to illiquidity risk, information uncertainty, and investors' lottery-like preferences.

To demonstrate the validity of our evidence in support of the limited-attention theory, we investigate whether the value premium is unrelated to these alternative explanations and whether the relation between limit-hit frequency and the value premium is robust to alternative information measures. The results reject the hypotheses associated with limits-to-arbitrage, illiquidity risk, and investors' lottery-like preferences in explaining the value premium. Nevertheless, some proxies still provide incremental explanatory ability to discriminate the return difference between value and growth stocks beyond the effect of limit-hit frequency. To ensure that our findings regarding limit-hit frequency are distinct from the alternative information measures, we compute the residual limit-hit frequency from a cross-sectional regression to isolate the information embedded in limit-hit frequency from other measures. Our results remain unchanged when we conduct analyses based on the residual limit-hit frequency, again strengthening the robustness of our findings.

Our study contributes to the asset-pricing literature by showing that the value premium has distinct driving forces in different markets. In particular, Ali, Hwang, and Trombley (2003) document strong evidence for limits-to-arbitrage in explaining the value premium in the U.S. market. That is, the U.S. evidence points to the mispricing explanation for the value premium. Our results, however, indicate that the existence of the value premium in Taiwan is induced because of investors' limited capacity to capture the information embedded in stock prices. This evidence is in favor of the limited attention hypothesis in capturing the value premium in Taiwan.

The rest of this paper is organized as follows. We develop the competing hypotheses regarding the relation between limit-hit frequency and the value premium in Section 2. Section 3 describes the data and constructions of variables used in this paper and demonstrates the existence of the value premium in Taiwan. Section 4 provides both cross-sectional regressions and portfolio-level analyses to comprehensively examine the impact of limit-hit frequency on the value premium. Section 5 investigates the incremental explanatory power of limit-hit frequency on the value premium controlling for the effects of several alternative explanations. The last section concludes this paper.

2. Literature review and hypotheses development

2.1. Limits-to-arbitrage and limit-hit frequency

Limits-to-arbitrage refers to a form of risk that impedes arbitrageurs from engaging in arbitrage activities to correct for potential mispricing. If asset-pricing anomalies are induced because of mispricing, their return premia will be strengthened among stocks with higher degrees of limits-to-arbitrage. The most widely adopted measure of limits-to-arbitrage in the literature is idiosyncratic volatility (Pontiff, 1996; Ali, Hwang, and Trombley, 2003; Wurgler and Zhuravskaya, 2002; Mashruwala, Rajgopal, and Shevlin, 2006; Lam and Wei, 2011; Lipson, Mortal, and Schill, 2011). In particular, idiosyncratic volatility has been considered to proxy for arbitrage risk in explaining the positive relation between BM ratio and stock returns (Ali, Hwang, and Trombley, 2003), the negative relation between accruals and stock returns (Mashruwala, Rajgopal, and Shevlin, 2006), and the negative relation between asset growth (AG) and stock returns (Lam and Wei, 2011; Lipson, Mortal, and Schill, 2011).

The literature also indicates that stocks with higher degrees of information uncertainty tend to be subject to higher degrees of limits-to-arbitrage. If the true value of a firm is more ambiguous, it is more difficult for arbitrageurs to eliminate potential arbitrage opportunities (Jiang, Lee, and Zhang, 2005). Firms with less analysts following (Hong, Lim, and Stein, 2000; Gleason and Lee, 2003; Zhang, 2006), higher dispersion in analysts' earnings forecasts (Diether, Malloy, and Scherbina, 2002; Zhang, 2006), and younger age (Zhang, 2006) tend to be less informative and are subject to higher degrees of information uncertainty.

Motivated by Chou, Chou, Ko, and Chao's (2013) argument that price limits represent implementation risk, a form of arbitrage risk, a positive relation between limit-hit frequency and limits-to-arbitrage can be expected. Presumedly, if a stock hits its limit prices more often, it is more difficult and riskier for arbitrageurs to correct for the potential mispricing. Limit-hit frequency is also related to information uncertainty because price limits can refrain the true price of a stock from being revealed, and a higher frequency of such event may cause higher degrees of price ambiguity or uncertainty of the true price.

Taking advantage of the observations that limit-hit frequency is positively correlated with limits-to-arbitrage and that market mispricing is a potential source of the value premium, we propose that limits-to-arbitrage could be a channel to establish the relation between limit-hit frequency and the value premium. This leads to our first testable hypothesis:

Hypothesis 1 (H_1): The hypothesis of limits-to-arbitrage predicts that the value premium is stronger among stocks with higher limit-hit frequency.

2.2. Limited investor attention and limit-hit frequency

Investor attention has important implications to the return dynamics that are associated with investors' underreaction to information. In particular, investors' limited attention can cause investors to ignore useful information, especially firms' earnings announcements, leading to subsequent underreaction to price changes. If the value premium is induced because of investors' underreaction to information, the return premia of asset-pricing anomalies should be more pronounced among stocks that receive less investor attention.

There is ample evidence indicating that both individual investors and professionals have limited attention (Hirst and Hopkins, 1998; Barber and Odean, 2008; Corwin and Coughenour, 2008). Trading volume (or turnover), size, and analyst coverage are generally used as proxies of limited attention in the literature. Among the vast studies, Lo and Wang (2000) show that trading volumes are higher among large stocks which tend to attract more investor attention. Chordia and Swaminathan (2000) suggest that trading volume contains information about investor attention that is not captured by size, and that trading volume is able to isolate return continuations and reversals in both short and long runs. Gervais, Kaniel, and Mingelgrin (2001) and Barber and Odean (2008) further provide supportive evidence that trading volume is directly related to investor attention.

Although trading volume has been widely adopted as the most popular proxy for investor attention, its information content may be noisy in a market with the imposition of price limits. On the one hand, whenever a stock hits its upper or lower price boundary, trading is allowed at the limit price, but not beyond. In such situation, trading volume will be limited even the stock has drawn investors' attention. Hence it is possible that attention-grabbing stocks generate lower trading volume at the limit price. On the other hand, the literature has also indicated that price limits might be triggered more frequently by the magnet effect (Cho, Russell, Tiao, and Tsay, 2003). The magnet effect suggests that stock price accelerates toward the limit prices as it gets closer to the limits. As a result, trading volume would increase irrationally right when the stock's price is approaching its limit price. However, whenever a stock's price is close to or at its limit prices, it may attract more investor attention, especially when the event occurs more frequently.

Empirical evidence also indicates that trading volume is related to value and liquidity strategies. Datar, Naik, and Radcliffe (1998) show that low turnover stocks generate higher returns than high turnover stocks, supporting the liquidity hypothesis of Amihud and Mendelson (1986). Lee and Swaminathan (2000) find that firms with high (low) turnover ratios exhibit many glamour (value) characteristics, inducing lower (higher) subsequent returns. To summarize, we hypothesize that trading volume is a noisy measure of investor attention while limit-hit frequency is a straightforward proxy of investor attention. Moreover, if the value premium is induced by investors' limited attention, limit-hit frequency could better capture the return patterns that are associated with the value strategy. This leads to the second testable hypothesis:

Hypothesis 2 (H_2): The limited-attention theory predicts that the value premium is stronger among stocks with lower limit-hit frequency.

3. Data and methodology

3.1. The evolution of price limit rules in Taiwan

A price limit refers to an upper or lower boundary of the previous day's closing price of a stock. When the TWSE was initiated in 1962, the price limits were set to be $+/-5\%$. That is, the upper and lower boundaries are 1.05 and 0.95 multiplied by the previous day's closing price, respectively. In 1989, the price limit rule was extended to $+/-7\%$ and further to $+/-10\%$ on June 1, 2015. During our sample period from July 1982 to December 2015, there were only some temporary changes that narrowed down the price limits to $+/-3.5\%$ due to the earthquake, the presidential election, financial crisis, and 9/11 attacks. Besides these short periods, the price limits were fixed to be $+/-5\%$ before January 1989, $+/-7\%$ during January 1989 to May 30, 2015, and $+/-10\%$ afterwards.

3.2. Data and definitions of variables

Our data comprise all common stocks listed on the TWSE, including OTC stocks, for the sample period from July 1982 to December 2015. We chose this sample period because the accounting data are available from the Taiwan Economic Journal (TEJ) only after 1981. Return and accounting data of individual stocks are obtained from the TEJ. Consistent with the conventional use in the literature, we exclude financial firms because of the high leverage for these firms. To be included in our final sample, firms are required to have more than two years history to avoid possible survivorship bias in the fundamental data. Over our sample period, the average number of stocks is 713, with 93 and 1,548 observations for July 1982 and December 2015, respectively.

We begin by introducing the definition of limit-hit frequency, which is the most important variable of this paper. At the beginning of each month t, we define limit-hit frequency (denoted as LF) as the number of days that stock i's closing price hits its up or down limit prices over past 12 months divided by the number of trading days during the same period, expressed as:

$$LF_{i,t} = \frac{number\ of\ days\ with\ price\ limits\ over\ past\ 12\ months\ for\ stock\ i}{number\ of\ trading\ days\ over\ past\ 12\ months\ for\ stock\ i}. \qquad (1)$$

Because higher proportion of limit-hit days implies higher value of LF, this measure is positively correlated with investor attention (or negatively correlated with limited attention). In addition, because price limits may represent a form of arbitrage risk that impedes arbitrageurs from engaging in arbitrage activities to correct for potential mispricing, LF also proxies for limits-to-arbitrage; i.e., higher value of LF implies higher degree of limits-to-arbitrage.

We consider 7 variables that have been documented to explain stock returns in the literature as candidate anomalies. We incorporate market beta (BETA) to consider the systematic risk. For every month t, we estimate BETA by obtaining the coefficient from the time-series regressions of monthly returns on the TAIEX (the proxy of the market index in Taiwan) in excess of the risk-free rate using past 5-year data up to month $t-1$ with at least 24 observations. We incorporate firm size (SIZE) and BM ratio because Fama and French (1992, 1998), among vast studies, indicate that the two anomalies are pronounced and important in both the U.S. and international stock markets. Following Fama and French (1992), for every June in a given year to July of next year, SIZE is defined as a firm's market capitalization at the end of June in that year, and BM is defined as the ratio of the book value of equity plus deferred taxes to the market value of equity measured at the end of the previous year. Although Fama and French (1992) show that the explanatory power of EP ratio is subsumed by BM, we still incorporate EP because we have yet examined whether there is a dominant value strategy in Taiwan. EP is defined as the ratio of earning per share to price measured at the end of the previous year. We include AG because Cooper, Gulen, and Schill (2008) and follow-up studies suggest the importance of corporate investments to future stock returns. We define AG as the growth rate on total assets measured at the end of the previous year. Novy-Marx (2013) proposes that gross profitability (GP) captures the complementary effect of the value strategy. We thus include GP, which is defined as gross profits (revenues minus cost of goods sold) scaled by total assets as of the end of the previous year. Finally, we include the cumulative return over past 12 months (PR12) to capture the momentum effect proposed by Jegadeesh and Titman (1993). To mitigate the influence of outliers, we follow Fama and French (1992) and Brennan, Chordia, and Subrahmanyam (1998) by setting the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile equal to the 0.995 and 0.005 fractile values, respectively.

In addition to LF, we also consider several measures from different explanations. The first variable is associated with limits-to-arbitrage, which is proxied by idiosyncratic volatility (denoted as IVOL). IVOL is widely adopted as the measure of limits-to-arbitrage in the literature (Ali, Hwang, and Trombley, 2003; Li and Zhang, 2010; Lam and Wei, 2011). For every month, IVOL is computed as the standard deviation of the residuals from the following time-series market model estimated with 36 months of observations ending in the previous month: $R_{i,t} = b_{i,0} + b_{i,1} R_{M,t} + e_{i,t}$, where $R_{i,t}$ is stock i's return in month t and $R_{M,t}$ is the return on the TAIEX in month t. The second variable is related to investor (in)attention, which is proxied by firms' turnover (denoted as TURNOVER). In standard case without price limits, higher value of TURNOVER signifies higher degree of investor attention (Hou, Peng, and Xiong, 2009). TURNOVER is defined as the time-series average of monthly share trading volume divided by the number of shares outstanding over the past 12 months ending in month $t-1$. Because the frequency of price limits may also be related to liquidity, we include Amihud's (2002) illiquid measure (denoted as ILLIQ) as the third variable to control for the illiquidity effect. ILLIQ is defined as the time-series average of daily Amihud measure over the past 12 months ending in month $t-1$, where the Amihud measure is calculated as the absolute daily returns divided by daily dollar trading volume.

Because information uncertainty is related to limits-to-arbitrage (Jiang, Lee, and Zhang, 2005; Zhang, 2006; Lam and Wei, 2011), we include firm age (denoted as AGE) as the fourth variable.[2] AGE is the number of years a stock has been established. Finally, if a stock hits limit prices more often, it has higher possibility to exhibit lottery-type payoffs. Hence we consider investors' lottery-like preferences as the fifth variable, with return skewness (denoted as SKEW) as the proxy. Zhang (2013) also demonstrates that skewness is

[2]Because we have no earnings forecast data for the Taiwan market, we do not include the number of analysts following and dispersion of in analysts' earnings forecasts as proxies of information uncertainty.

negatively related to firms' glamour/value feature and thus explains the value premium in the U.S. market. SKEW is defined as $\frac{1}{D_t}\sum_{d=1}^{D_t}(\frac{R_{i,d}-\mu_i}{\sigma_i})^3$, where D_t is the number of trading days over the past 12 months ending in month $t-1$; $R_{i,d}$ is stock i's return on day d; μ_i is the mean of i's daily returns over the past 12 months ending in month $t-1$; σ_i is the standard deviation of i's daily returns over the past 12 months ending in month $t-1$.

Panel A of Table 1 reports the summary statistics of variables. The average market capitalization of firms in Taiwan during our sample period is 11.013 billion. Individual firms on average have an EP ratio of 0.069 with a standard deviation of 0.051. The mean and standard deviation of BM (GP) are 0.630 and 0.886 (0.792 and 0.533), respectively. Among the 7 variables examined in this paper, SIZE, BM, AG, and PR12 display considerable skewness because their average values are remarkably higher than corresponding median values. To mitigate the effects of outliers, we take a natural logarithm on SIZE, BM, and 1+AG as independent variables in cross-sectional regression analyses. Moreover, the average percentage of limit-hit days is 10.8% across all sample firms and the corresponding standard deviation is 8.1%, suggesting a significant variation in LF across firms and over time.

[Insert Table 1 here]

Panel B presents the sample correlations between the variables. BM is negatively correlated with EP (the correlation is −0.046) and GP (the correlation is −0.160), leading to a positive correlation of 0.128 between EP and GP. The negative relation between BM and GP is consistent with the U.S. evidence documented in Novy-Marx (2013), who proposes that GP captures the complementary effect of the BM strategy. Moreover, the positive relation between EP and GP suggests that the explanatory power of EP may also be related to firm profitability. We also observe that LF is highly correlated with IVOL and TURNOVER with corresponding correlations of 0.670 and 0.418. This evidence confirms the dual role of limit-hit frequency in capturing different behavioral biases that are associated with limits-to-arbitrage and investor attention.

Another notable observation is the high correlation between TURNOVER and ILLIQ, which is −0.454. This is not surprising and confirms the literature that TURNOVER is a widely adopted proxy of liquidity (Datar, Naik, and Radcliffe, 1998; Lee and Swaminathan, 2000). The correlation between LF and ILLIQ, on the contrary, is quite low at 0.040, suggesting that limit-hit frequency is less prone to the illiquidity effect. Although Hou, Peng, and Xiong (2009) propose that TURNOVER captures the degree of investor attention, it is difficult to isolate the information embedded in TURNOVER that is associated with attention from stock liquidity. Our LF measure, however, is not subject to the liquidity effect and thus serves as a cleaner proxy of investor attention.

3.3. The existence of the value premium in Taiwan

We first adopt the Fama and MacBeth (1973) cross-sectional regressions to investigate whether the 7 candidate variables are priced in Taiwan. For every month, we perform the following cross-sectional regressions:

$$
\begin{aligned}
R_{i,t} \quad = \quad & \alpha_{0,t} + \alpha_{1,t} BETA_{i,t} + \alpha_{2,t} ln(SIZE_{i,t}) + \alpha_{3,t} ln(BM_{i,t}) + \alpha_{4,t} EP_{i,t} + \alpha_{5,t} ln(1 + AG_{i,t}) \\
& + \alpha_{6,t} GP_{i,t} + \alpha_{7,t} PR12_{i,t} + \varepsilon_{i,t}, \qquad (2)
\end{aligned}
$$

where $R_{i,t}$ is stock i's return in month t and the independent variables are defined as in Section 3.2. We then calculate and test the time-series averages of the monthly estimated coefficients from Equation (2) using t-statistics calculated based on the Newey and West (1987) robust standard errors.

In addition to raw returns, we also follow Brennan, Chordia, and Subrahmanyam's (1998) approach to obtain risk-adjusted returns. For each month t, we perform the following time-series regressions for each stock i:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t}, \tag{3}$$

where $R_{f,t}$ is the risk-free rate in month t, MKT_t is the return on the TAIEX in excess of the risk-free rate in month t, and SMB_t and HML_t are two mimicking portfolios formed on firm size and BM ratios in month t as in Fama and French (1993). We estimate Equation (3) using past 5-year data up to month $t-1$ with at least 24 observations and define risk-adjusted return on stock i as

$$R^*_{i,t} \equiv R_{i,t} - R_{f,t} - \hat{\beta}_{i,MKT}\lambda_{MKT,t} - \hat{\beta}_{i,SMB}\lambda_{SMB,t} - \hat{\beta}_{i,HML}\lambda_{HML,t}, \tag{4}$$

where $\lambda_{MKT,t}$, $\lambda_{SMB,t}$, and $\lambda_{HML,t}$ are corresponding factor realizations in month t. We then replace $R^*_{i,t}$ as the dependent variable in Equation (2) and repeat the testing procedures.

We report the estimation results of the Fama and MacBeth regressions for the full, January-only, and non-January samples in Table 2. The results indicate that the only significant anomaly in Taiwan is the EP effect, with the corresponding coefficient of 0.665 and a t-statistic of 2.78 using raw returns for the full sample. The positive relation between EP and stock return remains significant in non-January months and is insignificant in January months. In addition, the BETA coefficients are insignificant, indicating that the systematic risk is not priced in the Taiwan stock market and that the EP effect is not captured by the market risk.

[Insert Table 2 here]

We also show that the size, BM, AG, GP, and momentum effects are all absent in the Taiwan stock market. The only exception is the marginal significance of the GP anomaly under the Fama-French risk adjustments. In particular, the absence of the size and BM anomalies are consistent with Chen and Zhang (1998), Chui and Wei (1998), and Ding, Chua, and Fetherston (2005). The insignificant AG effect is consistent with Titman, Wei, and Xie (2013). In addition, the only significant phenomenon in January is the reversal of past 12-month returns. The January reversal pattern of the momentum strategy is consistent with the U.S. evidence documented in Jegadeesh and Titman (1993) and George and Hwang (2004). Finally, the significant coefficient on EP sustains when returns are adjusted by the Fama and French (1993) three-factor model. To summarize, the overall findings from Table 2 not only confirm the literature that the BM premium does not exist in Taiwan but also indicate that EP is the only profitable value strategy in this market.

4. Limit-hit frequency and the value premium

4.1. Characteristics of stocks by limit-hit frequency

Before formally examining the relation between limit-hit frequency and the value premium in Taiwan, we provide a preliminary analysis to observe the characteristics of stocks grouped by limit-hit frequency. For each month t, we classify individual stocks into three groups based on their values of LF. Within each LF group, we calculate the cross-sectional averages of variables described in Section 3.2. In addition to the variables examined in this paper, we also compute average monthly returns in month *t* after the calculation of LF and average return volatilities (denoted as SIGMA) of stocks. SIGMA is calculated as the standard deviation of daily stock returns over past 12 months. Table 3 reports the time-series averages of the cross-sectional means for each variable.

[Insert Table 3 here]

For the full sample period, the average proportions of days over past 12 months that a stock hits its limit prices are 4.8%, 9.0%, and 18.7% for low, median, and high LF groups. Among which, 2.9%, 5.5%, and 11.8% are up limit days (ULF) while 1.9%, 3.6%, and 6.9% are down limit days (DLF). This finding indicates that up price limits occur more often than down price limits in the Taiwan stock market. The average monthly returns are 0.974%, 1.433%, and 2.849%, indicating that stocks hitting their limit prices more often generate higher subsequent returns in general. In addition, confirming Kim and Limpaphayom's (2000) finding, we find that stocks with higher SIGMA, lower SIZE, and higher TURNOVER have higher values of LF. Consistent with the literature, high BETA stocks also hit their limit prices more often. Moreover, high LF stocks tend to have higher IVOL and low AGE and SKEW, consistent with the observation in Table 1.

The relation between LF and firm fundamentals is also worthy of investigation. We find that higher LF stocks have higher BM ratios and tend to be past winners, i.e., having higher PR12. We do not observe particular patterns for EP, AG, and GP across LF groups instead.

Thus the impact of LF on the cross-sectional of stock returns is more likely to be distinct from firm fundamentals such as EP, AG, and GP.

In addition to the full sample period, we also observe the patterns for subperiods of 1982/07-1988/12, 1989/01-2015/05, and 2015/06-2015/12, during which the price limit rules are $+/-5\%$, $+/-7\%$, and $+/-10\%$, respectively. The subsample results can be summarized as follows. First, LF, ULF, and DLF all become lower when the market adopts wider ranges of price limits. This observation is reasonable because it is easier for stocks to hit their limit prices if the boundaries are narrower. Second, Kim and Limpaphayom's (2000) finding that high LF stocks having higher SIGMA, lower SIZE, and higher TURNOVER is robust to the subperiods, indicating that investors' trading behavior is not affected by the changes in the price limit rules. Finally, the patterns of future returns, BM, PR12, IVOL, and AGE across LF groups are quite similar in different subperiods. The results from the subsample analyses indicate that the features of stocks grouped by limit-hit frequency do not change sharply when the price limit boundaries change over time. More importantly, the overall findings from Table 3 suggest that limit-hit frequency does display some similarities in firm characteristics and information measures. To isolate the differences between LF and alternative information measures, we provide robustness tests in Section 5 to control for these alternative explanations.

4.2. Cross-sectional regressions conditional on limit-hit frequency

To consider the effect of limit-hit frequency on asset-pricing anomalies in Taiwan, we follow the methods of Li and Zhang (2010) and Lam and Wei (2011) to adopt the Fama and MacBeth (1973) cross-sectional regressions separately for subsamples partitioned by LF.

For each month t, individual stocks are classified into three groups based on their values of LF. Within each LF group, we perform the cross-sectional regressions of Equation (2) using both raw and risk-adjusted returns as the dependent variables. Table 4 presents the results.

[Insert Table 4 here]

For the full sample period (Panel A), the average coefficient on EP in the low LF group is highly significant at 2.072 (t-statistic = 4.82); it decreases to 0.984 (t-statistic = 2.29) in the median LF group, and shrinks to a statistically insignificant 0.473 (t-statistic = 1.17) in the high LF group. This leads to a significant difference of −1.599 with a t-statistic of −2.79 between stocks with high and low values of LF. When returns are adjusted by the Fama and French (1993) factors, the corresponding coefficients become 1.953, 0.786, and 0.382 for low, median, and high LF groups with a difference of −1.571 (t-statistic = −2.67). Moreover, LF does not produce significant variation in other variables given that these anomalies are not priced in Taiwan. We also observe from Panels B and C that the impact of LF on the EP anomaly is concentrated in non-January months but not in January months. In particular, the monotonically decreasing pattern of the EP coefficient across LF groups exists only in non-January months and no significant variation is observable in January months.

Another notable finding from Table 4 is that the coefficients on BETA are all insignificant across LF groups regardless of risk adjustments. Although the literature indicates that stocks with high BETA hit price limits more frequently, we do not observe particular pattern between market risk and stock returns across LF groups. More importantly, the negative relation between the EP anomaly and LF is robust to the consideration of the market risk, thus ruling out the possibility that our finding is driven by risk compensation.

So far, we measure the frequency of price limit days based on both events of up and down price limits. To demonstrate the robustness of our findings, we consider the possible asymmetric effects of price limits by separating the effects of up and down price limit events. Specifically, we define LF_UP (LF_DOWN) as the number of days that stock i's closing price hits its up (down) limit prices over past 12 months divided by the number of trading days during the same period. We then classify individual stocks into three groups based on their values of LF_UP or LF_DOWN and perform the cross-sectional regressions of Equation (2) separately for the subsamples. We report the estimation results in Table 5.

[Insert Table 5 here]

Panel A indicates that the EP effect is stronger among stocks with lower LF_UP, regardless of risk adjustments. For raw returns, the coefficients on EP are 2.046, 1.220, and 0.156 for low, median, and high LF_UP stocks with a difference of −1.890 (t-statistic = −3.17) between high and low LF_UP groups. It is also the case for the LF_DOWN measure, as shown in Panel B, with corresponding coefficients of 1.748, 1.210, and 0.695 and a difference of −1.053 (t-statistic = −2.09). The results suggest that our evidence is robust to the way we define limit-hit frequency. More importantly, the overall results from Tables 4 and 5 implicitly point to the limited-attention hypothesis (H_2) in explaining the value premium in Taiwan because the return difference between high and low EP stocks is higher among those that infrequently hit their limit prices.

4.3. Portfolio analyses

In addition to cross-sectional regressions, we also adopt portfolio analyses to observe the magnitude of the value premium conditional on limit-hit frequency. For each month t, we allocate individual stocks into three groups according to their values of LF and subdivide them into quintiles according to their values of EP within each LF group. We calculate equally- and value-weighted returns for each of the 15 LF-EP sorted portfolios in month t. The portfolios are rebalanced every month. We then calculate the EP premium as the return difference between highest and lowest EP portfolios for each LF group. In addition to raw returns, we also obtain intercepts from the time-series regressions of portfolio returns on the Fama and French (1993) three-factor model as risk-adjusted returns. Table 6 reports raw and risk-adjust returns of portfolios, with Panels A and B presenting the results based on equal and value weights, respectively.

[Insert Table 6 here]

We show that the EP premium is significant only in the low LF group. For equally-weighted portfolios, the raw returns of the EP strategy are 0.648%, 0.322%, and −0.402% for low, median, and high LF groups; the corresponding risk-adjusted returns are 0.781%, 0.324%, and −0.362%, respectively. This pattern remains the same and even stronger when the value-weighted scheme is applied. The overall results reveal higher EP premium for stocks with lower values of LF. Thus, our evidence in support of the limited-attention hypothesis in explaining the EP anomaly is robust to different empirical methods.

4.4. Abnormal trading volume and limit-hit frequency

Although our results regarding limit-hit frequency and the value premium is consistent with the prediction of the limited-attention hypothesis, no direct linkage between our findings and investors' limited attention has been established so far. To confirm that our results are in support of the limited-attention hypothesis, we examine whether price limit events induce abnormal trading volume of stocks.[3] This investigation is motivated by Barber and Odean's (2008) observation that high abnormal trading volume is an important feature for attention-grabbing stocks. We follow Barber and Odean (2008) by defining abnormal trading volume ($AV_{i,d}$) for stock i on day d as the ratio of the stock's trading volume on day d to its average trading volume over the previous 252 trading days ending in day $d-1$, which is expressed as

$$AV_{i,d} = \frac{V_{i,d}}{\overline{V}_{i,d}}, \tag{5}$$

where $V_{i,d}$ is stock i's dollar volume traded on day d and $\overline{V}_{i,d} = \sum_{k=d-252}^{d-1} \frac{V_{i,k}}{252}$. Intuitively, higher value of $AV_{i,d}$ indicates higher abnormal volume and thus signifies higher degree of investor attention. We compute $AV_{i,d}$ over trading days $d-5$ to $d+5$ surrounding every price limit event for every individual stock. We then compute the averages and medians of $AV_{i,d-5}$ to $AV_{i,d+5}$ across all price limit events for all stocks. As a comparison, we also calculate $AV_{i,d-5}$ to $AV_{i,d+5}$ for every non-hit trading day to observe whether limit-hit events exhibit different patterns on abnormal volume. Panel A of Table 7 reports the results.

[Insert Table 7 here]

[3]We acknowledge the anonymous referee for pointing out this important issue.

Several interesting findings emerge from Panel A of Table 7. First, before the limit-hit day, the average abnormal volume ranges from 1.911 (on day $t - 5$) to 2.408 (on day $t - 1$) while the median abnormal volume ranges from 0.667 (on day $t - 5$) to 0.765 (on day $t - 1$). On the limit-hit day, the average (median) abnormal volume increases substantially to 3.312 (1.051), drifts to 3.769 (1.161) on day $t + 1$, and further decreases gradually to 2.289 (0.826) on day $t + 5$. Second, for non-hit days, the average (median) abnormal volume ranges from 1.143 (0.520) to 1.316 (0.535), and no particular pattern is observable. Finally, compared with non-hit abnormal volume, limit-hit abnormal volume is always higher for all days surrounding each day d. These results confirm our conjecture that price limits induce higher abnormal volume surrounding the occurrence of the price limit events. That is, our results establish a direct linkage between price limits and investor attention in Taiwan.

We next establish the relation between limit-hit frequency and investor attention by examining whether our limit-hit frequency measure is correlated with abnormal volume. To this end, for every month t we calculate the average $AV_{i,d}$ for every stock using all trading days (denoted as TAV), limit-hit days (denoted as HAV), and non-hit days (denoted as NAV) over past 12 months ending in month $t - 1$. Within each of the three LF groups, we calculate the cross-sectional averages on TAV, HAV, and NAV and report the time-series averages of these cross-sectional means. We also calculate and test the differences on TAV, HAV, and NAV between high and low LF groups. If limit-hit frequency does capture the degree of investor attention, we expect that abnormal volume would be significantly higher in high LF group than in the low LF group.

Panel B of Table 7 confirms our conjecture. For the TAV measure which is calculated using all trading days, the average values are 1.450, 1.597, and 2.661 for low, median, and high LF groups with a difference of 1.210 ($t - statistic = 6.12$). Similar patterns are also observable in HAV and NAV measures. This evidence suggests that during the formation period of LF, stocks that hit their limit prices more often also have higher abnormal volumes and thus capture investors' attention. Stocks that have low tendency to hit their limit prices, however, have lower abnormal volumes and are subject to the limited attention from investors. This evidence provides a direct linkage between limit-hit frequency and investor attention and thus supports our conjecture that investors' limited attention is the main reason to underly the value premium in Taiwan.

4.5. Limit-hit frequency as a market-wide attention measure

Our main results indicate that limit-hit frequency is an important determinant to capture the variations of stock returns in the cross-section, and that its explanatory power is stronger when investors pay less attention to such stock. In addition to its explanatory power in the cross-section, it is also important to examine whether limit-hit frequency contain information about the overall attentiveness of the market; that is, if limit-hit frequency could be an useful market-wide measure of investor attention. Specifically, we propose that when more firms hit their limit prices in a given period of time, investors' attention to the stock market would be higher during this period. As a result, the value premium would be insignificant during such period if it is driven by the limited-attention theory. Also, it implies that the value premium during periods of low investor inattention would be stronger and significant.

To examine this issue, we follow a similar procedure adopted by Amihud (2002), Pástor and Stambaugh (2003), and Liu (2006) to measure market-wide attentiveness based on the concept of aggregate LF. For every month t, we calculate the monthly average of LF (denoted as MKT_LF) across all sample firms. MKT_LF thus represents the overall proportion of days that sample firms hit their price limits over past 12 months. If this average ratio is high, investors' attention to the overall market would be enhanced because price limit events occurred more frequently. We use the 50% cutoff point to identify the level of market-wide attentiveness. If MKT_LF in a given month t is greater (smaller) than the cutoff point, we define this month as high (low) attention period. We then perform the Fama and MacBeth (1973) regressions of Equation (2) separately for periods of high and low attention and report the estimation results in Panel A of Table 8.

[Insert Table 8 here]

We confirm our hypothesis by showing that the EP premium is significant only for low attention periods but not for high attention periods. The corresponding EP coefficients based on raw returns are 1.046 (t-statistic = 3.23) and 0.298 (t-statistic = 0.89) for low and high attention periods, respectively. This pattern remains unchanged when risk-adjusted returns are applied. In addition to EP, we also observe significant coefficient on GP for low attention periods, suggesting that not only the EP effect but also the GP anomaly exists when investors pay less attention to the stock market. Despite this, the magnitude and significance of the EP coefficient are more pronounced than those of the GP coefficient during low attention periods. This finding indicates that the EP premium remains the most profitable value strategy when we consider different time-period effects.

In addition to cross-sectional regressions, we also adopt portfolio-based analyses to observe the impact of MKT_LF on the EP premium over time. For every month, we construct the EP strategy by forming decile EP portfolios and then hold the highest EP portfolio and short sell the lowest EP portfolio. We calculate the average monthly returns of the EP strategy with value weights separately for periods of low and high investor attention and report the results in Panel B of Table 8. Consistent with the findings in Panel A, the EP strategy generates a remarkably high profit of 1.077% (t-statistic = 2.37) per month during low attention periods and an insignificant profit of −0.088% (t-statistic = −0.13) per month during high attention periods. The corresponding risk-adjusted returns are 0.962% and 0.319%, respectively. The results lead to an important implication that limit-hit frequency not only captures the cross-sectional variations of the EP premium but also measures market-wide attentiveness over time.

5. Limit-hit frequency versus alternative explanations

5.1. Results based on alternative information measures

Although our main results based on limit-hit frequency are consistent with the prediction of limited-attention theory, we cannot rule out the possibility that alternative explanations based on other information measures may also account for the profitability of the EP strategy. To this end, we contrast our results with alternative explanations by replicating the cross-sectional regressions of Equation (2) conditional on IVOL, TURNOVER, ILLIQ, AGE, and SKEW, respectively. In particular, if it is the limits-to-arbitrage hypothesis to explain the EP premium, we expect a higher coefficient on EP for high IVOL stocks. If turnover is a good proxy of investor attention, the limited-attention theory predicts a higher coefficient on EP among low TURNOVER stocks. Stocks with higher ILLIQ have higher coefficient on EP if illiquidity risk explains the EP anomaly. If the EP anomaly is related to information uncertainty, low AGE stocks should generate higher EP premium. Finally, Zhang (2013) proposes that investors' lottery-like preference has strong impact on the value premium, implying that the EP anomaly is stronger among stocks with lower values of SKEW. We test these alternative explanations by performing cross-sectional regressions separately for each of the three groups formed by these information measures. We report the average coefficients on EP in Table 9, and the results are summarized and discussed as follows.

[Insert Table 9 here]

First, we document no evidence for the limits-to-arbitrage hypothesis in explaining the value premium. For raw returns, the coefficient estimates on EP are 1.970, 1.343, and 1.147 for low, median, and high IVOL groups, respectively. The results based on risk-adjusted returns are virtually the same with those based on raw returns. Given its high correlation with LF, we cannot rule out the possibility that the monotonically decreasing pattern of EP coefficients across IVOL groups is affected by investors' limited attention. This finding also indicates that Ali, Hwang, and Trombley's (2003) result of positive relation between the value premium and the limitation of arbitrage activities does not apply to the Taiwan stock market.

Second, although Hou, Peng, and Xiong (2009) propose that TURNOVER can be a proxy for investor attention, our results based on TURNOVER do not conform to the limited-attention hypothesis in explaining the value premium. The EP coefficient displays a monotonically increasing pattern as TURNOVER increases. In particular, the corresponding coefficients are 0.669, 0.956, and 1.952 for low, median, and high TURNOVER groups with a difference of 1.283 (t-statistic = 2.39) between high and low TURNOVER groups. This difference is 1.035 (t-statistic = 1.62) under risk adjustments. The inconsistency between the use of TURNOVER and the prediction of the limited-attention hypothesis may be partly attributed to the fact that TURNOVER is highly correlated with ILLIQ (the correlation is −0.454 from Table 1). The positive relation between TURNOVER and the EP premium suggests that the value premium is stronger among more liquid stocks. In addition, when a stock hits its price limit, trading is allowed at the limit price but not beyond. This would cause high attention but low trading volume if price limits occur more often. As a result, TURNOVER may contain information related to liquidity and is unable to correctly capture the degree of investor attention.

Third, the results based on ILLIQ strengthen our conjecture that stock liquidity enhances the profitability of the EP anomaly in Taiwan. The EP coefficient is 2.547 in the low ILLIQ group, decreases to 1.435 in the median ILLIQ group, and further shrinks to 0.481 in the high ILLIQ group, resulting in a difference of −2.067 with a t-statistic of −2.92 between high and low ILLIQ groups. More importantly, the negative relation between ILLIQ and the EP coefficient suggests that the EP premium is not driven by the illiquidity risk.

Fourth, the EP premium is shown to be related to information uncertainty, which is observable from the monotonically decreasing EP coefficients across AGE groups. For risk-adjusted returns, the EP coefficient is significant only in the low AGE group but not beyond. The evidence that younger firms yield higher EP premium is also consistent with the limited-attention hypothesis because younger firms in general receive fewer attention than older firms.

Finally, we show that investors' lottery-like preferences do not account for the EP premium. The coefficient on EP for the high SKEW group is significantly higher than that for the low SKEW group regardless of risk adjustments. The differences are 1.635 (t-statistic = 4.24) and 1.194 (t-statistic = 2.09) for raw and risk-adjusted returns, respectively. This positive relation between SKEW and the EP premium contradicts Zhang's (2013) prediction that the value premium is explained by investors' preference for positive skewness.

To summarize, our results indicate that limits-to-arbitrage, illiquidity risk, and investors' lottery-like preferences fail to properly account for the profitability of the EP strategy in Taiwan. The results based on firm age, however, is rather consistent with the prediction of the limited-attention hypothesis. As a further test, we examine in next subsection whether these alternative variables provide incremental explanatory ability to discriminate the return differences between value and growth stocks beyond the effect of limit-hit frequency.

5.2. Results conditional on limit-hit frequency and alternative information measures

To investigate how the alternative variables interact with limit-hit frequency in explaining the EP premium, we adopt a dependent sorting procedure that involves LF and each of the alternative variables including IVOL, TURNOVER, ILLIQ, AGE, and SKEW. For each month, we first allocate individual stocks into three groups according to their values of LF and subdivide each LF group into terciles according to the values of different information measures. For each of the nine groups, we perform the cross-sectional regressions of Equation (2) and report the results in Table 10.

[Insert Table 10 here]

Panels A, B, and E indicate that the significantly positive coefficient on EP for low LF stocks exists in all IVOL/TURNOVER/SKEW groups, suggesting that the relation between LF and the EP premium is robust to the consideration of the IVOL/TURNOVER/SKEW effect. The significantly positive coefficients on EP for low LF stocks are also found to be concentrated in high and low ILLIQ (Panel C) and younger AGE (Panel D) groups. Most importantly, the significantly positive coefficients on EP are concentrated in the low LF group in most cases of the five alternative measures. The overall evidence from Table 10 suggests that the five information measures provide very limited explanatory power on the value premium beyond the effect of limit-hit frequency.

5.3. The residual limit-hit frequency

Although the results based on alternative information measures documented in previous subsections do not support corresponding hypotheses in explaining the value premium, they do produce considerable variations to discriminate the value premium beyond the effect of limit-hit frequency. To ensure that our evidence regarding limit-hit frequency is distinct from these information measures, we compute residual limit-hit frequency (denoted RES_LF) from a cross-sectional regression of LF on these variables:

$$\begin{aligned} LF_{i,t} \quad = \quad & \delta_{0,t} + \delta_{1,t} IVOL_{i,t} + \delta_{2,t} TURNOVER_{i,t} + \delta_{3,t} ILLIQ_{i,t} + \delta_{4,t} AGE_{i,t} \\ & + \delta_{5,t} SKEW_{i,t} + \varepsilon_{i,t}^{LF}. \end{aligned} \tag{6}$$

We define RES_LF as $\varepsilon_{i,t}^{LF}$ for stock i in month t. For each month, we classify individual stocks into three groups based on their values of RES_LF and perform Equation (2) for each RES_LF group. Table 11 gives the estimation results.

[Insert Table 11 here]

Compared with the results shown in Table 4, we obtain statistically similar findings in Table 11. That is, even when we eliminate the information related to the five information measures, the residual information embedded in LF is still powerful to explain the EP premium. More importantly, the results based on RES_LF are consistent with the prediction of the limited-attention theory in explaining the value premium in Taiwan.

6. Conclusion

Given the ample literature focusing on the pros and cons of price limits, this paper provides the first investigation to understand whether and how price limits are related to the cross-section of stock returns. Motivated by Kim and Limpaphayom's (2000) empirical evidence that stocks with higher degrees of behavioral characteristics hit limit prices more often, we propose a measure of limit-hit frequency to explain the cross-sectional variations of stock returns. By construction, limit-hit frequency represents a dual role of behavioral biases; one is associated with limits-to-arbitrage and the other is associated with investor attention. We propose competing hypotheses regarding limits-to-arbitrage and limited-attention theories to examine the impact of limit-hit frequency on stock returns.

The anomaly we focus on is the EP anomaly, which is the only pronounced value strategy in Taiwan. Taking limit-hit frequency into consideration, we find that the EP premium is remarkably stronger among stocks that hit their limit prices less frequently than those with higher limit-hit frequency. This finding is robust to risk adjustments, alternative definitions of limit-hit frequency, and different empirical methods. A further test reveals that limit-hit frequency captures not only cross-sectional variations of the EP premium but also the time-varying patterns of the anomaly. These results lead us in believing that investors' limited attention is the underlying reason of the EP premium in Taiwan.

We also show that limits-to-arbitrage, illiquidity risk, and investors' lottery-like preferences are unlikely to be the main reason behind the value premium, while information uncertainty seems to provide plausible room to contribute to the anomaly. However, even if we control for the effects of these information measures, the residual information embedded in limit-hit frequency still retains its explanatory power for the value premium. Given a long debate on the pros and cons of price limits, our study contributes to the literature by providing the first investigation to establish the robust linkage between price limits and asset-pricing anomalies in the Taiwan stock market.

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Table 1: Summary statistics and correlation matrix of variables

This table reports summary statistics and correlation matrix of variables for all common stocks listed on the TWSE over the period from July 1982 to December 2015. BETA is a firm's systematic risk estimated from the market model. SIZE is a firm's market capitalization at the end of June in that year. BM is the ratio of the book value of equity plus deferred taxes to the market value of equity measured at the end of the previous year. EP is the ratio of earning per share to price measured at the end of the previous year. AG is the growth rate on total assets measured at the end of the previous year. GP is gross profits (revenues minus cost of goods sold) scaled by total assets. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. PR12 is the cumulative return over past 12 months. LF is the number of days that a stock's closing price hits its up- or down-limit prices over past 12 months divided by the number of trading days during the same period. IVOL is the standard deviation of the residuals from the market model estimated with 36 months of observations ending in the previous month. TURNOVER is the time-series average of monthly share trading volume divided by the number of shares outstanding over the past 12 months ending in month $t-1$. ILLIO is the time-series average of daily Amihud measure over the past 12 months ending in month $t-1$. AGE is the number of years a stock has been established. SKEW is defined as $\frac{1}{D_t}\sum_{d=1}^{D_t}(\frac{R_{i,d}-\mu_i}{\sigma_i})^3$, where D_t is the number of trading days over the past 12 months ending in month $t-1$; $R_{i,d}$ is stock i's return on day d; μ_i is the mean of i's daily returns over the past 12 months ending in month $t-1$; σ_i is the standard deviation of i's daily returns over the past 12 months ending in month $t-1$. Panel A reports the time-series averages of cross-sectional statistics of variables, while Panel B reports correlations between variables.

Variable	BETA	SIZE	BM	EP	AG	GP	PR12	LF	IVOL	TURNOVER	ILLIQ	AGE	SKEW
Panel A: Summary statistics of variables													
Mean	1.220	11.013	0.630	0.069	0.125	0.792	0.234	0.108	15.162	24.037	0.022	25.321	0.298
Median	1.192	3.867	0.425	0.064	0.077	0.698	0.112	0.090	13.999	18.401	0.001	24.099	0.207
Std. Dev.	1.688	29.609	0.886	0.051	0.319	0.533	0.723	0.081	6.123	20.909	0.141	10.666	0.994
Max	10.047	297.998	9.224	0.756	3.497	3.513	7.242	0.688	62.557	131.861	2.167	54.721	9.354
Min	−5.715	0.167	0.062	0.001	−0.441	0.005	−0.761	0.009	5.273	0.070	0.000	4.305	−5.467
Panel B: Correlations between variables													
BETA	1	0.060	0.033	0.005	0.001	−0.033	−0.009	0.068	0.094	0.121	−0.102	−0.015	−0.014
SIZE		1	−0.321	0.029	0.252	−0.014	0.168	−0.257	−0.285	0.053	−0.564	0.148	0.009
BM			1	−0.046	−0.326	−0.160	0.010	0.214	0.062	0.002	0.086	0.205	−0.012
EP				1	0.049	0.128	0.019	−0.159	−0.122	−0.077	0.020	−0.031	0.030
AG					1	0.141	0.060	−0.104	−0.096	0.108	−0.125	−0.165	0.030
GP						1	0.060	−0.108	−0.159	0.001	0.105	−0.155	0.025
PR12							1	0.024	−0.048	0.129	0.066	0.047	0.031
LF								1	0.670	0.418	0.040	−0.149	−0.172
IVOL									1	0.343	0.054	−0.182	−0.191
TURNOVER										1	−0.454	−0.116	−0.177
ILLIQ											1	−0.108	0.098
AGE												1	0.007
SKEW													1

Table 2: Fama-MacBeth cross-sectional regressions

For every month over the period from July 1982 to December 2015, we perform the following cross-sectional regressions:

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}BETA_{i,t} + \alpha_{2,t}ln(SIZE_{i,t}) + \alpha_{3,t}ln(BM_{i,t}) + \alpha_{4,t}EP_{i,t} + \alpha_{5,t}ln(1 + AG_{i,t}) + \alpha_{6,t}GP_{i,t} + \alpha_{7,t}PR12_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $BETA_{i,t}$ is a firm's systematic risk estimated from the market model; $ln(SIZE_{i,t})$ is the natural logarithm of a firm's market capitalization; $ln(BM_{i,t})$ is the natural logarithm of a firm's BM ratio; $EP_{i,t}$ is the ratio of a firm's earning per share to price; $AG_{i,t}$ is firm's growth rate on total assets; $PR12_{i,t}$ is a firm's cumulative return over past 12 months. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. We use raw and Fama-French risk-adjusted returns as the dependent variable, respectively. We then report and test the time-series averages of the monthly estimated coefficients from the cross-sectional regressions separately for the full sample, January-only and non-January subsamples. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns			Fama-French-adjusted returns		
Variable	All	Jan.	Non-Jan.	All	Jan.	Non-Jan.
Intercept	2.358*	7.648**	1.885	1.666	5.067	1.362
	(1.93)	(2.24)	(1.52)	(1.27)	(1.28)	(1.03)
BETA	0.017	0.251	−0.004	−0.352***	−0.148	−0.370***
	(0.33)	(1.12)	(−0.09)	(−3.02)	(−0.52)	(−2.94)
ln(SIZE)	−0.163	−0.420	−0.140	−0.148	−0.073	−0.155
	(−1.47)	(−1.03)	(−1.27)	(−1.29)	(−0.16)	(−1.36)
ln(BM)	0.141	1.301	0.038	−0.099	1.552	−0.246
	(0.72)	(1.16)	(0.21)	(−0.49)	(1.35)	(−1.25)
EP	0.665***	−0.504	0.769***	0.537**	−0.555	0.635**
	(2.78)	(−0.80)	(3.12)	(2.16)	(−0.88)	(2.49)
ln(1+AG)	−0.137	1.223	−0.259	−0.049	0.271	−0.078
	(−0.27)	(0.92)	(−0.50)	(−0.09)	(0.20)	(−0.14)
GP	0.229	−0.326	0.278*	0.327*	−0.101	0.365**
	(1.49)	(−0.70)	(1.78)	(1.85)	(−0.19)	(2.06)
PR12	−0.392	−3.073**	−0.153	−0.385	−3.575**	−0.100
	(−1.12)	(−2.36)	(−0.42)	(−1.02)	(−2.52)	(−0.26)

Table 3: Characteristics of stocks by limit-hit frequency

This table reports average firm characteristics of stocks grouped by limit-hit frequency. For each month t, we classify individual stocks into three groups based on their values of LF. Within each LF group, we calculate the cross-sectional averages of characteristics. We then report the time-series averages of the cross-sectional means. LF is the number of days that a stock's closing price hits its up- or down-limit prices over past 12 months divided by the number of trading days during the same period. ULF (DLF) is the number of days that a stock's closing price hits its up- (down-) limit prices over past 12 months divided by the number of trading days during the same period. $R_{i,t}$ is stock i's return in month t. SIGMA is the standard deviation of daily stock returns over past 12 months. BETA is a firm's systematic risk estimated from the market model. SIZE is a firm's market capitalization at the end of June in that year. BM is the ratio of the book value of equity plus deferred taxes to the market value of equity measured at the end of the previous year. EP is the ratio of earning per share to price measured at the end of the previous year. AG is the growth rate on total assets measured at the end of the previous year. GP is gross profits (revenues minus cost of goods sold) scaled by total assets. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. PR12 is the cumulative return over past 12 months. IVOL is the standard deviation of the residuals from the market model estimated with 36 months of observations ending in the previous month. TURNOVER is the time-series average of monthly share trading volume divided by the number of shares outstanding over the past 12 months ending in month $t-1$. ILLIO is the time-series average of daily Amihud measure over the past 12 months ending in month $t-1$. AGE is the number of years a stock has been established. SKEW is defined as $\frac{1}{D_t}\sum_{d=1}^{D_t}(\frac{R_{i,d}-\mu_i}{\sigma_i})^3$, where D_t is the number of trading days over the past 12 months ending in month $t-1$; $R_{i,d}$ is stock i's return on day d; μ_i is the mean of i's daily returns over the past 12 months ending in month $t-1$; σ_i is the standard deviation of i's daily returns over the past 12 months ending in month $t-1$. In addition to the full sample, we also report the results for subperiods of 1982/07-1988/12, 1989/01-2015/05, and 2015/06-2015/12.

	Full period			1982/07-1988/12			1989/01-2015/05			2015/06-2015/12		
LF group	Low	Median	High	Low	Median	High	Low	Median	High	Low	Median	High
LF	0.048	0.090	0.187	0.088	0.133	0.254	0.040	0.083	0.176	0.002	0.014	0.056
ULF	0.029	0.055	0.118	0.054	0.081	0.158	0.024	0.050	0.111	0.001	0.009	0.038
DLF	0.019	0.036	0.069	0.034	0.052	0.097	0.016	0.033	0.065	0.001	0.004	0.018
$R_{i,t}$	0.974	1.433	2.849	4.172	3.360	4.435	0.354	1.089	2.597	−1.095	−1.170	−0.707
SIGMA	5.359	6.452	8.633	4.267	4.911	7.007	5.637	6.819	9.014	3.051	4.358	6.699
BETA	1.048	1.299	1.299	−0.251	0.145	−0.291	1.339	1.557	1.648	0.137	0.485	0.475
SIZE	16.528	9.808	6.543	4.337	4.762	4.061	18.880	10.802	7.081	24.989	12.348	5.545
BM	0.137	0.209	0.936	0.432	0.490	0.612	0.083	0.159	1.011	0.154	0.042	0.574
EP	0.072	0.066	0.068	0.079	0.068	0.070	0.072	0.066	0.068	0.072	0.062	0.056
AG	0.132	0.135	0.107	0.066	0.063	−0.065	0.147	0.152	0.143	0.060	0.063	0.083
GP	0.839	0.797	0.739	0.860	0.827	0.523	0.837	0.793	0.786	0.696	0.686	0.673
PR12	0.174	0.201	0.350	0.500	0.528	0.444	0.112	0.139	0.339	−0.090	−0.118	−0.037
IVOL	11.613	14.503	19.427	9.861	11.328	16.639	12.083	15.271	20.119	6.822	9.618	14.404
TURNOVER	14.524	26.613	34.764	16.465	28.532	29.625	14.331	26.594	36.202	4.967	9.382	18.100
ILLIQ	0.020	0.012	0.035	0.039	0.027	0.053	0.017	0.009	0.032	0.002	0.001	0.007
AGE	27.202	25.411	23.359	25.890	22.862	24.187	27.325	25.871	23.154	34.022	28.633	24.853
SKEW	0.365	0.281	0.247	0.458	0.177	0.185	0.344	0.298	0.254	0.423	0.483	0.509

Table 4: Fama-MacBeth regressions conditional on limit-hit frequency

For every month over the period from July 1982 to December 2015, we define LF as the number of days that stock i's closing price hits its up- or down-limit prices over past 12 months divided by the number of trading days during the same period. We then classify individual stocks into three groups based on their values of LF. Within each LF group, we perform the following cross-sectional regressions:

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}BETA_{i,t} + \alpha_{2,t}ln(SIZE_{i,t}) + \alpha_{3,t}ln(BM_{i,t}) + \alpha_{4,t}EP_{i,t} + \alpha_{5,t}ln(1 + AG_{i,t}) + \alpha_{6,t}GP_{i,t} + \alpha_{7,t}PR12_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $BETA_{i,t}$ is a firm's systematic risk estimated from the market model; $ln(SIZE_{i,t})$ is the natural logarithm of a firm's market capitalization; $ln(BM_{i,t})$ is the natural logarithm of a firm's BM ratio; $EP_{i,t}$ is the ratio of a firm's earning per share to price; $AG_{i,t}$ is firm's growth rate on total assets; $PR12_{i,t}$ is a firm's cumulative return over past 12 months. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. We use raw and Fama-French risk-adjusted returns as the dependent variable, respectively. We then report and test the time-series averages of the monthly estimated coefficients from the cross-sectional regressions. Panels A to C present the estimation results for the full sample, January-only and non-January subsamples, respectively. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns				Fama-French-adjusted returns			
Variable	Low	Median	High	High-Low	Low	Median	High	High-Low
Panel A: All months								
Intercept	2.917**	3.178**	2.880*	−0.037	2.215	1.945	2.012	−0.202
	(2.29)	(2.21)	(1.75)	(−0.03)	(1.60)	(1.29)	(1.12)	(−0.14)
BETA	−0.021	0.040	−0.014	0.008	−0.278*	−0.372***	−0.356***	−0.077
	(−0.29)	(0.82)	(−0.19)	(0.08)	(−1.95)	(−2.90)	(−2.91)	(−0.63)
ln(SIZE)	−0.272**	−0.278**	−0.217	0.054	−0.257**	−0.223	−0.191	0.066
	(−2.35)	(−1.98)	(−1.27)	(0.37)	(−2.00)	(−1.60)	(−1.02)	(0.41)
ln(BM)	0.150	0.395	0.072	−0.078	−0.057	0.069	−0.130	−0.073
	(0.62)	(1.48)	(0.25)	(−0.24)	(−0.20)	(0.22)	(−0.43)	(−0.19)
EP	2.072***	0.984**	0.473	−1.599***	1.953***	0.786*	0.382	−1.571***
	(4.82)	(2.29)	(1.17)	(−2.79)	(4.09)	(1.81)	(1.05)	(−2.67)
ln(1+AG)	−0.556	−0.275	−2.043	−1.487	−0.616	0.306	−2.104	−1.488
	(−1.08)	(−0.68)	(−1.14)	(−0.79)	(−1.02)	(0.59)	(−1.19)	(−0.78)
GP	−0.101	0.293	−0.041	0.060	−0.100	0.607**	0.153	0.253
	(−0.52)	(1.49)	(−0.11)	(0.16)	(−0.45)	(2.45)	(0.39)	(0.61)
PR12	−0.124	−0.652	−0.073	0.050	0.032	−0.468	−0.037	−0.069
	(−0.22)	(−1.13)	(−0.15)	(0.08)	(0.06)	(−0.85)	(−0.07)	(−0.11)
Panel B: January months								
Intercept	7.771**	7.662**	8.177	0.406	6.918	5.161	5.836	−1.082
	(2.05)	(2.51)	(1.55)	(0.08)	(1.48)	(1.38)	(0.98)	(−0.19)
BETA	0.146	0.101	0.323	0.177	0.006	−0.339	−0.231	−0.237
	(0.77)	(0.39)	(1.32)	(0.79)	(0.02)	(−0.85)	(−0.76)	(−1.04)
ln(SIZE)	−0.564	−0.448	−0.307	0.257	−0.372	−0.129	0.057	0.429
	(−1.34)	(−1.15)	(−0.48)	(0.45)	(−0.78)	(−0.30)	(0.08)	(0.68)
ln(BM)	0.975	0.920	1.738	0.763	1.986	1.147	1.732	−0.254
	(0.82)	(0.89)	(1.11)	(0.65)	(1.66)	(1.00)	(1.09)	(−0.21)
EP	1.090	0.057	−1.088	−2.177	1.036	−0.740	−0.877	−1.913
	(0.77)	(0.05)	(−0.87)	(−1.18)	(0.66)	(−0.53)	(−0.65)	(−1.00)
ln(1+AG)	0.750	−0.026	0.316	−0.435	0.147	−1.724	−0.636	−0.783
	(0.54)	(−0.02)	(0.11)	(−0.13)	(0.11)	(−1.21)	(−0.22)	(−0.25)
GP	0.045	−0.204	−0.735	−0.781	0.447	0.290	−0.896	−1.343
	(0.08)	(−0.29)	(−0.56)	(−0.66)	(0.87)	(0.35)	(−0.63)	(−0.99)
PR12	−2.536*	−3.233**	−3.037*	−0.501	−2.760**	−3.547**	−3.318*	−0.557
	(−1.87)	(−2.30)	(−1.81)	(−0.37)	(−2.19)	(−2.26)	(−1.80)	(−0.41)

Table 4 continued

Variable	Raw returns				Fama-French-adjusted returns			
	Low	Median	High	High-Low	Low	Median	High	High-Low
Panel C: Non-January months								
Intercept	2.483*	2.777*	2.406	−0.077	1.794	1.657	1.670	−0.124
	(1.88)	(1.90)	(1.45)	(−0.06)	(1.24)	(1.07)	(0.92)	(−0.09)
BETA	−0.036	0.034	−0.044	−0.007	−0.304*	−0.375***	−0.367***	−0.063
	(−0.48)	(0.71)	(−0.61)	(−0.07)	(−1.91)	(−2.75)	(−2.87)	(−0.48)
ln(SIZE)	−0.246**	−0.263*	−0.209	0.036	−0.247*	−0.232	−0.213	0.034
	(−2.07)	(−1.86)	(−1.21)	(0.24)	(−1.84)	(−1.62)	(−1.13)	(0.20)
ln(BM)	0.076	0.348	−0.077	−0.153	−0.240	−0.028	−0.296	−0.056
	(0.31)	(1.24)	(−0.28)	(−0.45)	(−0.81)	(−0.08)	(−0.98)	(−0.14)
EP	2.160***	1.067**	0.613	−1.548**	2.035***	0.922**	0.494	−1.540**
	(4.74)	(2.39)	(1.40)	(−2.50)	(4.05)	(2.00)	(1.29)	(−2.47)
ln(1+AG)	−0.673	−0.298	−2.254	−1.581	−0.684	0.487	−2.236	−1.551
	(−1.27)	(−0.69)	(−1.19)	(−0.80)	(−1.08)	(0.89)	(−1.20)	(−0.77)
GP	−0.114	0.338*	0.021	0.136	−0.149	0.636**	0.247	0.396
	(−0.55)	(1.70)	(0.06)	(0.34)	(−0.62)	(2.52)	(0.62)	(0.89)
PR12	0.092	−0.421	0.191	0.100	0.282	−0.192	0.256	−0.026
	(0.15)	(−0.67)	(0.40)	(0.14)	(0.53)	(−0.33)	(0.51)	(−0.04)

Table 5: Fama-MacBeth regressions conditional on alternative definitions of limit-hit frequency

For every month over the period from July 1982 to December 2015, we define LF_UP (LF_DOWN) as the number of days that stock i's closing price hits its up (down) limit price over past 12 months divided by the number of trading days during the same period. We then classify individual stocks into three groups based on their values of LF_UP (LF_DOWN). Within each LF_UP (LF_DOWN) group, we perform the following cross-sectional regressions:

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}BETA_{i,t} + \alpha_{2,t}ln(SIZE_{i,t}) + \alpha_{3,t}ln(BM_{i,t}) + \alpha_{4,t}EP_{i,t} + \alpha_{5,t}ln(1 + AG_{i,t}) + \alpha_{6,t}GP_{i,t} + \alpha_{7,t}PR12_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $BETA_{i,t}$ is a firm's systematic risk estimated from the market model; $ln(SIZE_{i,t})$ is the natural logarithm of a firm's market capitalization; $ln(BM_{i,t})$ is the natural logarithm of a firm's BM ratio; $EP_{i,t}$ is the ratio of a firm's earning per share to price; $AG_{i,t}$ is firm's growth rate on total assets; $PR12_{i,t}$ is a firm's cumulative return over past 12 months. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. We use raw and Fama-French risk-adjusted returns as the dependent variable, respectively. We then report and test the time-series averages of the monthly estimated coefficients from the cross-sectional regressions. Panels A and B present the estimation results conditional on LF_UP and LF_DOWN, respectively. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns				Fama-French-adjusted returns			
Variable	Low	Median	High	High-Low	Low	Median	High	High-Low
Panel A: Up price limits								
Intercept	2.107*	3.986**	2.653*	0.546	1.453	2.709	1.920	0.466
	(1.78)	(2.41)	(1.73)	(0.39)	(1.13)	(1.57)	(1.05)	(0.29)
BETA	0.010	0.026	−0.046	−0.056	−0.269**	−0.408***	−0.377**	−0.109
	(0.17)	(0.51)	(−0.49)	(−0.55)	(−2.06)	(−3.17)	(−2.51)	(−0.82)
ln(SIZE)	−0.191*	−0.353**	−0.155	0.036	−0.185	−0.259*	−0.124	0.061
	(−1.71)	(−2.42)	(−0.93)	(0.21)	(−1.52)	(−1.78)	(−0.63)	(0.30)
ln(BM)	0.024	0.460*	0.423	0.399	−0.198	0.306	0.273	0.471
	(0.10)	(1.85)	(1.08)	(0.94)	(−0.68)	(1.12)	(0.67)	(0.97)
EP	2.046***	1.220***	0.156	−1.890***	1.900***	0.869*	0.212	−1.687***
	(4.62)	(2.60)	(0.36)	(−3.17)	(4.00)	(1.93)	(0.49)	(−2.70)
ln(1+AG)	−0.627	−0.481	−0.198	0.429	−0.392	0.078	−0.117	0.275
	(−1.15)	(−1.14)	(−0.26)	(0.51)	(−0.63)	(0.14)	(−0.16)	(0.30)
GP	0.076	0.103	0.149	0.073	0.060	0.507**	0.245	0.185
	(0.45)	(0.56)	(0.41)	(0.19)	(0.31)	(2.09)	(0.64)	(0.46)
PR12	0.079	−0.637	−0.262	−0.341	0.248	−0.384	−0.164	−0.411
	(0.13)	(−0.94)	(−0.58)	(−0.48)	(0.45)	(−0.67)	(−0.37)	(−0.64)
Panel B: Down price limits								
Intercept	2.713**	3.088**	1.742	−0.971	2.387*	1.582	1.575	−0.812
	(2.32)	(2.03)	(1.01)	(−0.72)	(1.83)	(0.97)	(0.85)	(−0.54)
BETA	0.021	0.062	0.019	−0.002	−0.252*	−0.318**	−0.389***	−0.138
	(0.28)	(1.15)	(0.28)	(−0.02)	(−1.84)	(−2.57)	(−2.96)	(−1.21)
ln(SIZE)	−0.225**	−0.233	−0.174	0.051	−0.223*	−0.164	−0.189	0.034
	(−1.97)	(−1.58)	(−1.08)	(0.34)	(−1.69)	(−1.08)	(−1.07)	(0.21)
ln(BM)	0.246	0.348	−0.007	−0.253	0.233	0.051	−0.224	−0.457
	(1.04)	(1.43)	(−0.02)	(−0.77)	(0.82)	(0.19)	(−0.69)	(−1.19)
EP	1.748***	1.210***	0.695*	−1.053**	1.827***	1.178**	0.714**	−1.113**
	(4.56)	(2.84)	(1.90)	(−2.09)	(4.40)	(2.37)	(2.06)	(−2.10)
ln(1+AG)	0.019	−0.686*	−1.415	−1.434	0.182	−0.380	−1.322	−1.505
	(0.04)	(−1.69)	(−1.23)	(−1.14)	(0.29)	(−0.75)	(−1.16)	(−1.12)
GP	0.099	0.189	0.082	−0.018	0.091	0.371	0.251	0.160
	(0.54)	(1.01)	(0.28)	(−0.05)	(0.42)	(1.65)	(0.80)	(0.42)
PR12	0.041	−0.311	−1.248	−1.289*	0.352	−0.382	−0.909	−1.261**
	(0.09)	(−0.67)	(−1.41)	(−1.79)	(0.81)	(−0.69)	(−1.40)	(−2.05)

Table 6: Portfolio returns formed on EP ratios conditional on limit-hit frequency

For every month over the period from July 1982 to December 2015, we allocate individual stocks into three groups according to their values of LF and subdivide them into quintiles according to their values of EP within each LF group. We calculate equally- and value-weighted returns for each of the 15 LF-EP sorted portfolios in month *t*. The portfolios are rebalanced monthly and EP is fixed from June in a given year to July in next year. We then calculate the EP premium as the return difference between highest and lowest EP portfolios within each LF group. In addition to raw returns, we also obtain intercepts from the time-series regressions of portfolio returns on the Fama and French (1993) three-factor model as risk-adjusted returns. Panels A and B report the portfolio returns using equal and value weights, respectively. Numbers in the parentheses are the *t*-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns				Fama-French-adjusted returns			
Portfolio	Low	Median	High	High-Low	Low	Median	High	High-Low
Panel A: Equally-weighted returns								
Growth	1.249**	1.773**	2.215**	0.966*	0.959*	1.468**	1.664**	0.705
	(2.08)	(2.55)	(2.45)	(1.81)	(1.86)	(2.32)	(2.09)	(1.42)
2	1.098**	1.326**	1.180	0.082	0.877*	1.000*	0.775	−0.102
	(2.17)	(2.14)	(1.61)	(0.20)	(1.83)	(1.73)	(1.14)	(−0.27)
3	1.592***	1.250**	0.740	−0.851**	1.328***	0.924	0.356	−0.971**
	(3.19)	(2.16)	(1.05)	(−2.01)	(2.83)	(1.63)	(0.54)	(−2.45)
4	1.559***	1.535***	1.221*	−0.339	1.389***	1.286**	0.781	−0.608
	(3.29)	(2.80)	(1.89)	(−1.00)	(3.05)	(2.42)	(1.21)	(−1.61)
Value	1.897***	2.094***	1.813***	−0.085	1.740***	1.792***	1.302**	−0.438
	(3.83)	(3.86)	(2.86)	(−0.24)	(3.87)	(3.37)	(2.07)	(−1.15)
Value−Growth	0.648**	0.322	−0.402	−1.051*	0.781***	0.324	−0.362	−1.143**
	(2.27)	(0.88)	(−0.68)	(−1.88)	(2.81)	(0.97)	(−0.66)	(−2.21)
Panel B: Value−weighted returns								
Growth	1.153*	1.398**	1.685**	0.532	0.857	1.079	1.240	0.383
	(1.80)	(2.05)	(2.08)	(1.05)	(1.60)	(1.65)	(1.63)	(0.76)
2	0.829*	0.768	0.532	−0.297	0.576	0.401	0.159	−0.416
	(1.68)	(1.26)	(0.74)	(−0.64)	(1.18)	(0.69)	(0.23)	(−0.93)
3	1.236***	0.928	0.463	−0.773	0.975**	0.653	0.095	−0.880*
	(2.64)	(1.61)	(0.67)	(−1.59)	(2.06)	(1.14)	(0.14)	(−1.87)
4	1.288***	1.229**	1.103*	−0.185	1.102**	0.965*	0.623	−0.479
	(2.67)	(2.28)	(1.73)	(−0.50)	(2.36)	(1.81)	(0.95)	(−1.15)
Value	1.897***	1.842***	1.498**	−0.399	1.835***	1.558***	0.917	−0.918**
	(3.87)	(3.33)	(2.21)	(−0.90)	(3.95)	(2.89)	(1.36)	(−1.97)
Value−Growth	0.744*	0.444	−0.187	−0.931	0.978***	0.480	−0.324	−1.302**
	(1.89)	(1.02)	(−0.34)	(−1.64)	(2.80)	(1.16)	(−0.63)	(−2.49)

Table 7: Abnormal trading volume and limit-hit frequency

For every trading day d, we follow Barber and Odean (2008) by defining abnormal trading volume ($AV_{i,d}$) for stock i as the ratio of the stock's trading volume on day d to its average trading volume over the previous 252 trading days ending in day $d-1$, which is expressed as $AV_{i,d} = \frac{V_{i,d}}{\overline{V}_{i,d}}$, where $V_{i,d}$ is stock i's dollar volume traded on day d and $\overline{V}_{i,d} = \sum_{k=d-252}^{d-1} \frac{V_{i,k}}{252}$. Panel A reports the abnormal volume surrounding price limit events. We compute $AV_{i,d}$ over trading days $d-5$ to $d+5$ surrounding every price limit event for every individual stock. We then compute the averages and medians of $AV_{i,d-5}$ to $AV_{i,d+5}$ across all price limit events for all stocks. As a comparison, we also calculate $AV_{i,d-5}$ to $AV_{i,d+5}$ for every non-hit trading day. Panel B reports the average abnormal volume for each LF group. At the beginning of each month t, we calculate the average $AV_{i,d}$ for every stock using all trading days (denoted as TAV), limit-hit days (denoted as HAV), and non-hit days (denoted as NAV) over past 12 months. For our sample period from July 1982 to December 2015, we define LF as the number of days that stock i's closing price hits its up- or down-limit prices over past 12 months divided by the number of trading days during the same period. We classify individual stocks into three groups based on their values of LF. Within each LF group, we calculate the cross-sectional averages on TAV, HAV, and NAV and report the time-series averages of these cross-sectional means. We also calculate and test the differences on TAV, HAV, and NAV between high and low LF groups. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Category	Statistic	−5	−4	−3	−2	−1	0	1	2	3	4	5
Panel A: Abnormal volume surrounding price limit days												
Limit-hit days	Mean	1.911	1.941	2.083	2.091	2.408	3.312	3.769	3.177	2.717	2.480	2.289
	Median	0.667	0.681	0.701	0.727	0.765	1.051	1.161	0.971	0.893	0.852	0.826
Non-hit days	Mean	1.316	1.266	1.302	1.235	1.264	1.167	1.156	1.143	1.215	1.181	1.243
	Median	0.535	0.534	0.533	0.530	0.529	0.522	0.520	0.524	0.526	0.527	0.528

Abnormal volume measure	Low	Median	High	High−Low	
Panel B: Abnormal volume by LF groups					
All trading days (TAV)	1.450	1.597	2.661	1.210	***
				(6.12)	
Limit-hit days (HAV)	5.178	5.753	6.882	1.704	***
				(2.87)	
Non-hit days (NAV)	1.229	1.217	2.232	1.003	***
				(3.57)	

Table 8: Fama-MacBeth regressions and portfolio returns in high and low attention periods

For every month over the period from July 1982 to December 2015, we define LF as the number of days that stock i's closing price hits its up- or down-limit prices over past 12 months divided by the number of trading days during the same period. We then calculate the monthly average of LF across all individual stocks. We define a month as high (low) attention periods if the market-wide LF measure is above (below) the median of the whole time series. In Panel A, we perform the following cross-sectional regressions separately for periods of high and low investor attention:

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}BETA_{i,t} + \alpha_{2,t}ln(SIZE_{i,t}) + \alpha_{3,t}ln(BM_{i,t}) + \alpha_{4,t}EP_{i,t} + \alpha_{5,t}ln(1 + AG_{i,t}) + \alpha_{6,t}GP_{i,t} + \alpha_{7,t}PR12_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $BETA_{i,t}$ is a firm's systematic risk estimated from the market model; $ln(SIZE_{i,t})$ is the natural logarithm of a firm's market capitalization; $ln(BM_{i,t})$ is the natural logarithm of a firm's BM ratio; $EP_{i,t}$ is the ratio of a firm's earning per share to price; $AG_{i,t}$ is firm's growth rate on total assets; $PR12_{i,t}$ is a firm's cumulative return over past 12 months. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. We use raw and Fama-French risk-adjusted returns as the dependent variable, respectively. We then report and test the time-series averages of the monthly estimated coefficients from the cross-sectional regressions. In Panel B, we allocate individual stocks into deciles according to their values of EP and calculate value-weighted returns for each of the decile portfolios in month t. The portfolios are rebalanced monthly and EP is fixed from June in a given year to July in next year. We then calculate the EP premium as the return difference between highest and lowest EP portfolios separately for periods of high and low investor attention. In addition to raw returns, we also obtain intercepts from the time-series regressions of portfolio returns on the Fama and French (1993) three-factor model as risk-adjusted returns. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns		Fama-French-adjusted returns	
Variable	Low attention	High attention	Low attention	High attention
Panel A: Fama-MacBeth regressions				
Intercept	0.565	4.078**	−0.172	3.430
	(0.48)	(2.02)	(−0.13)	(1.62)
BETA	0.037	−0.003	−0.258**	−0.443**
	(0.94)	(−0.03)	(−2.02)	(−2.41)
ln(SIZE)	−0.065	−0.257	−0.060	−0.232
	(−0.57)	(−1.39)	(−0.48)	(−1.23)
ln(BM)	0.111	0.171	−0.178	−0.023
	(0.50)	(0.52)	(−0.75)	(−0.07)
EP	1.046***	0.298	1.093***	0.004
	(3.23)	(0.89)	(3.08)	(0.01)
ln(1+AG)	−0.142	−0.133	0.126	−0.217
	(−0.37)	(−0.14)	(0.29)	(−0.23)
GP	0.272	0.187	0.375*	0.281
	(1.62)	(0.74)	(1.91)	(0.99)
PR12	0.500	−1.248**	0.041	−0.794
	(1.28)	(−2.27)	(0.08)	(−1.40)
Panel B: Portfolio returns				
Growth	0.669	1.893	0.565	1.070
	(0.96)	(1.64)	(0.91)	(0.96)
2	0.191	0.959	0.024	0.233
	(0.31)	(0.92)	(0.04)	(0.23)
3	0.755	1.175	0.507	0.573
	(1.41)	(1.34)	(1.04)	(0.63)
4	1.158**	1.590*	0.954**	1.021
	(2.31)	(1.76)	(2.07)	(1.08)
Value	1.745***	1.806**	1.527***	1.389*
	(2.87)	(2.12)	(2.82)	(1.70)
Value−Growth	1.077**	−0.088	0.962**	0.319
	(2.37)	(−0.13)	(2.14)	(0.49)

Table 9: Fama-MacBeth regressions conditional on alternative information measures

For every month over the period from July 1982 to December 2015, we classify individual stocks into three groups based on their values of different information measures. The information measures include idiosyncratic volatility (IVOL), turnover (TURNOVER), the Amihud illiquid measure (ILLIQ), firm age (AGE), and return skewness (SKEW). Within each information measure group, we perform the following cross-sectional regressions:

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}BETA_{i,t} + \alpha_{2,t}ln(SIZE_{i,t}) + \alpha_{3,t}ln(BM_{i,t}) + \alpha_{4,t}EP_{i,t} + \alpha_{5,t}ln(1 + AG_{i,t}) + \alpha_{6,t}GP_{i,t} + \alpha_{7,t}PR12_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $BETA_{i,t}$ is a firm's systematic risk estimated from the market model; $ln(SIZE_{i,t})$ is the natural logarithm of a firm's market capitalization; $ln(BM_{i,t})$ is the natural logarithm of a firm's BM ratio; $EP_{i,t}$ is the ratio of a firm's earning per share to price; $AG_{i,t}$ is firm's growth rate on total assets; $PR12_{i,t}$ is a firm's cumulative return over past 12 months. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. We use raw and Fama-French risk-adjusted returns as the dependent variable, respectively. We then report the coefficient estimates on EP for each information measure group and test whether the time-series averages of the monthly estimated coefficients are significantly different from zero. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Alternative	Raw returns				Fama-French-adjusted returns			
measure	Low	Median	High	High-Low	Low	Median	High	High-Low
IVOL	1.970***	1.343***	1.147***	−0.823	1.826***	1.077**	0.823	−1.003
	(5.27)	(2.60)	(2.80)	(−1.48)	(4.51)	(2.08)	(1.64)	(−1.51)
TURNOVER	0.669**	0.956**	1.952***	1.283**	0.359	1.113***	1.394**	1.035
	(2.11)	(2.46)	(3.96)	(2.39)	(1.03)	(2.64)	(2.40)	(1.62)
ILLIQ	2.547***	1.435***	0.481*	−2.067***	2.246***	1.030**	0.391	−1.856**
	(3.45)	(3.44)	(1.91)	(−2.92)	(2.81)	(2.28)	(1.22)	(−2.41)
AGE	0.947**	0.819**	0.504	−0.444	0.959*	0.356	0.567	−0.393
	(2.15)	(2.54)	(1.30)	(−0.77)	(1.95)	(0.86)	(1.36)	(−0.59)
SKEW	0.433*	0.932**	2.068***	1.635***	0.525	0.645	1.719***	1.194**
	(1.68)	(1.97)	(5.61)	(4.24)	(1.43)	(1.17)	(3.81)	(2.09)

Table 10: Fama-MacBeth regressions conditional on limit-hit frequency and alternative information measures

For every month over the period from July 1982 to December 2015, we first allocate individual stocks into three groups according to their values of LF and subdivide each LF group into terciles according to the values of different information measures. The information measures include idiosyncratic volatility (IVOL), turnover (TURNOVER), the Amihud illiquid measure (ILLIQ), firm age (AGE), and return skewness (SKEW). Within each of the nine groups, we perform the following cross-sectional regressions:

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}BETA_{i,t} + \alpha_{2,t}ln(SIZE_{i,t}) + \alpha_{3,t}ln(BM_{i,t}) + \alpha_{4,t}EP_{i,t} + \alpha_{5,t}ln(1 + AG_{i,t}) + \alpha_{6,t}GP_{i,t} + \alpha_{7,t}PR12_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $BETA_{i,t}$ is a firm's systematic risk estimated from the market model; $ln(SIZE_{i,t})$ is the natural logarithm of a firm's market capitalization; $ln(BM_{i,t})$ is the natural logarithm of a firm's BM ratio; $EP_{i,t}$ is the ratio of a firm's earning per share to price; $AG_{i,t}$ is firm's growth rate on total assets; $PR12_{i,t}$ is a firm's cumulative return over past 12 months. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. We use raw and Fama-French risk-adjusted returns as the dependent variable, respectively. We then report the coefficient estimates on EP for each information measure group and test whether the time-series averages of the monthly estimated coefficients are significantly different from zero. Panels A to E present the estimation results regarding IVOL, TURNOVER, ILLIQ, AGE, and SKEW, respectively. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Alternative measure	Raw returns: Low	Raw returns: Median	Raw returns: High	Raw returns: High-Low	Fama-French-adjusted returns: Low	Fama-French-adjusted returns: Median	Fama-French-adjusted returns: High	Fama-French-adjusted returns: High-Low
Panel A: Subsamples split by LF and IVOL								
Low IVOL	1.506***	1.390*	1.058	−0.448	1.647***	1.417*	1.234	−0.413
	(2.93)	(1.91)	(1.23)	(−0.48)	(3.03)	(1.86)	(1.39)	(−0.42)
Median IVOL	1.289**	0.677	1.025	−0.263	1.383**	1.519	1.839*	0.456
	(2.05)	(0.72)	(1.10)	(−0.26)	(2.03)	(1.59)	(1.72)	(0.41)
High IVOL	1.708**	0.311	2.558	0.849	2.081**	−0.325	2.233	0.152
	(2.16)	(0.29)	(1.36)	(0.41)	(2.20)	(−0.24)	(1.40)	(0.08)
Panel B: Subsamples split by LF and TURNOVER								
Low TURNOVER	2.104***	0.206	0.292	−1.812	2.535***	0.378	0.681	−1.855
	(3.22)	(0.33)	(0.30)	(−1.58)	(3.15)	(0.44)	(0.67)	(−1.45)
Median TURNOVER	0.991**	2.177***	0.972	−0.019	1.091**	1.953**	−0.153	−1.245
	(2.28)	(3.02)	(1.20)	(−0.02)	(2.00)	(2.46)	(−0.09)	(−0.68)
High TURNOVER	2.051***	2.214***	1.619	−0.432	2.084**	2.820***	1.244	−0.840
	(3.42)	(2.99)	(1.61)	(−0.38)	(2.53)	(2.75)	(1.17)	(−0.64)
Panel C: Subsamples split by LF and ILLIQ								
Low ILLIQ	1.508*	1.820	−6.089	−7.597	1.962**	1.266	−13.694	−15.656
	(1.97)	(1.12)	(−0.71)	(−0.88)	(2.45)	(0.76)	(−0.95)	(−1.08)
Median ILLIQ	0.372	0.119	1.217	0.845	0.362	1.074	1.646	1.285
	(0.71)	(0.14)	(1.29)	(0.82)	(0.58)	(1.35)	(0.98)	(0.74)
High ILLIQ	1.922***	0.253	0.630	−1.293	6.820*	−0.441	0.563	−6.183
	(3.25)	(0.50)	(1.10)	(−1.59)	(1.73)	(−0.34)	(0.81)	(−1.52)
Panel D: Subsamples split by LF and AGE								
Small SIZE	2.246***	0.952	1.617	−0.629	3.470***	2.241**	2.073	−1.397
	(2.97)	(1.25)	(1.62)	(−0.54)	(2.99)	(2.07)	(0.97)	(−0.63)
Median SIZE	1.318**	0.848	0.527	−0.791	1.785***	1.244	−0.207	−1.992
	(2.34)	(1.25)	(0.68)	(−0.92)	(2.64)	(1.28)	(−0.16)	(−1.35)
Large SIZE	0.158	−0.083	−0.948	−1.106	0.110	0.288	−0.993	−1.103
	(0.25)	(−0.10)	(−0.80)	(−0.87)	(0.14)	(0.33)	(−0.58)	(−0.60)
Panel E: Subsamples split by LF and SKEW								
Low DVOL	1.303**	1.292*	1.772	0.469	1.292	2.356**	4.637*	3.345
	(2.27)	(1.79)	(1.30)	(0.32)	(1.40)	(2.11)	(1.74)	(1.18)
Median DVOL	1.432**	−0.394	−0.310	−1.742**	1.344**	0.018	−0.351	−1.695
	(2.54)	(−0.54)	(−0.38)	(−2.01)	(2.06)	(0.02)	(−0.22)	(−1.06)
High DVOL	2.412***	0.884	0.352	−2.060	3.180***	2.396***	−0.669	−3.849
	(4.15)	(1.05)	(0.27)	(−1.47)	(4.58)	(2.73)	(−0.24)	(−1.34)

Table 11: Fama-MacBeth regressions conditional on residual limit-hit frequency

For every month over the period from July 1982 to December 2015, we define LF as the number of days that stock i's closing price hits its up- or down-limit prices over past 12 months divided by the number of trading days during the same period. We compute residual limit-hit frequency denoted RES_LF from a cross-sectional regression of LF on several variables:

$$LF_{i,t} = \delta_{0,t} + \delta_{1,t}IVOL_{i,t} + \delta_{2,t}TURNOVER_{i,t} + \delta_{3,t}ILLIQ_{i,t} + \delta_{4,t}AGE_{i,t} + \delta_{5,t}SKEW_{i,t} + \varepsilon^{LF}_{i,t}.$$

We define RES_LF as $\varepsilon^{LF}_{i,t}$ for stock i in month t. and classify individual stocks into three groups based on their values of RES_LF. Within each RES_LF group, we perform the following cross-sectional regressions:

$$R_{i,t} = \alpha_{0,t} + \alpha_{1,t}BETA_{i,t} + \alpha_{2,t}ln(SIZE_{i,t}) + \alpha_{3,t}ln(BM_{i,t}) + \alpha_{4,t}EP_{i,t} + \alpha_{5,t}ln(1 + AG_{i,t}) + \alpha_{6,t}GP_{i,t} + \alpha_{7,t}PR12_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is stock i's return in month t; $BETA_{i,t}$ is a firm's systematic risk estimated from the market model; $ln(SIZE_{i,t})$ is the natural logarithm of a firm's market capitalization; $ln(BM_{i,t})$ is the natural logarithm of a firm's BM ratio; $EP_{i,t}$ is the ratio of a firm's earning per share to price; $AG_{i,t}$ is firm's growth rate on total assets; $PR12_{i,t}$ is a firm's cumulative return over past 12 months. To mitigate the influence of outliers, the values of SIZE, BM, EP, AG, and GP greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. We use raw and Fama-French risk-adjusted returns as the dependent variable, respectively. We then report and test the time-series averages of the monthly estimated coefficients from the cross-sectional regressions. Numbers in the parentheses are the t-statistics calculated using the Newey-West (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns				Fama-French-adjusted returns			
Variable	Low	Median	High	High-Low	Low	Median	High	High-Low
Intercept	1.000	1.470	2.313	1.313	0.966	0.420	1.159	0.192
	(0.76)	(1.01)	(1.56)	(0.94)	(0.62)	(0.26)	(0.70)	(0.13)
BETA	0.034	0.074	0.038	0.005	−0.318***	−0.263**	−0.284**	0.034
	(0.56)	(1.30)	(0.50)	(0.06)	(−2.70)	(−1.99)	(−2.17)	(0.36)
ln(SIZE)	−0.106	−0.150	−0.140	−0.034	−0.130	−0.084	−0.082	0.048
	(−0.89)	(−1.19)	(−0.84)	(−0.21)	(−0.95)	(−0.57)	(−0.46)	(0.26)
ln(BM)	0.202	0.148	0.151	−0.051	0.121	−0.228	−0.061	−0.182
	(0.96)	(0.60)	(0.45)	(−0.16)	(0.50)	(−0.83)	(−0.17)	(−0.48)
EP	1.336***	1.475***	0.604*	−0.731	1.363***	1.265**	0.426	−0.937*
	(3.68)	(3.36)	(1.79)	(−1.61)	(2.61)	(2.52)	(1.27)	(−1.66)
ln(1+AG)	0.137	−0.048	−0.571	−0.708	0.510	−0.242	−0.293	−0.803
	(0.29)	(−0.11)	(−0.70)	(−0.77)	(0.86)	(−0.42)	(−0.33)	(−0.76)
GP	0.543**	0.269	0.219	−0.324	0.572**	0.199	0.396	−0.176
	(2.48)	(1.38)	(0.76)	(−0.97)	(2.24)	(0.85)	(1.21)	(−0.46)
PR12	−0.772	−1.178	−0.453	0.319	−0.745	−1.166*	−0.461	0.283
	(−1.18)	(−1.61)	(−0.92)	(0.44)	(−1.18)	(−1.72)	(−0.95)	(0.43)