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Speculative Retail Trading and Asset Prices

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Abstract

This paper examines the characteristics and pricing of stocks that are actively traded by speculative retail investors. We find that stocks with high retail trading proportion (RTP) have strong lottery features and they attract retail investors with strong gambling propensity. Furthermore, these stocks tend to be overpriced and earn significantly negative alpha. The average monthly return differential between the extreme RTP quintiles is −0.60%. This negative RTP premium is stronger among stocks that have lottery features or are located in regions where people exhibit stronger gambling propensity. Collectively, these results indicate that speculative retail trading affects stock prices.

I. Introduction

Speculative trading is one of the hallmarks of financial markets. Recent studies in behavioral finance indicate that certain investors, especially some retail investors, are drawn toward stocks with speculative features such as high skewness and high volatility (e.g., Kumar (2009), Dorn and Huberman (2010)). In a search for extreme returns, speculators may be willing to undertake large amounts of short-term risk even if those investments yield lower average returns. Such behavior stands in clear contrast to the implications of traditional models of risk and return. However, it is consistent with some investors' desire to gamble or preference for skewness (e.g., Shefrin and Statman (2000), Barberis and Huang (2008)), to seek sensation or entertainment in trading (e.g., Grinblatt and Keloharju (2009), Dorn and Sengmueller (2009)).

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Speculative stocks would also attract investors who derive extra nonwealth utility from the act of realizing gains. Barberis and Xiong (2012) present a model in which investors with realization utility exhibit risk-seeking behavior. These investors may hold and trade more frequently high-volatility stocks because those stocks offer a greater chance of realizing gains.

Motivated by these earlier studies, we examine whether speculative trading activities of retail investors affect asset prices. In the first part of the paper, we show that the set of stocks in which speculation-induced trading levels are high can be successfully characterized by the retail trading proportion (RTP) measure. The RTP of a stock is defined as the monthly dollar value of the buy- and sell-initiated small trades (trade size below $5,000) divided by the dollar value of its total trading volume in the same month. The small-trades data are obtained from the Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) data sets, where small trades are used as a proxy for retail trades. Our trading-based measure of retail habitat is motivated by the observation that investors buy and sell the stocks within their habitat more frequently. By comparing the RTP variable with actual retail holdings and trading data from a discount brokerage house, we demonstrate that RTP closely captures the preferences and trading activities of retail investors.

Cross-sectional analysis reveals that speculative stock attributes are important determinants of the level of retail trading in a stock. In particular, stocks with high idiosyncratic volatility (IVOL) and skewness or lower prices are predominately held and actively traded by retail investors, while institutional investors underweight those stocks. We also find that the characteristics of the retail clienteles of high-RTP stocks are very similar to the characteristics of investors who exhibit greater propensity to speculate and gamble as documented in Kumar (2009). Furthermore, the RTP is significantly higher for firms that are headquartered in regions in which people exhibit a greater propensity to gamble. Collectively, these results indicate that retail speculation is an important driver of trading in high-RTP stocks.

In additional tests, we find that high levels of retail trading are at least partially related to the activities of investors who derive an additional positive non-wealth utility from the act of realizing gains. Specifically, consistent with the prediction of the realization utility model of Barberis and Xiong (2012), we show that investors' propensity to realize gains is stronger among high-volatility stocks. In addition, we demonstrate that a significant positive relation exists between the proportion of retail trading in a stock and investors' propensity to realize gains.

Taken together, these results from the 1st part of our paper indicate that RTP captures speculative retail trading. High-RTP stocks have strong lottery features. They are the preferred habitat of retail investors who exhibit a stronger propensity to gamble and risk-seeking investors who derive an extra nonwealth utility when they realize gains.

In the 2nd part of the paper, we examine asset pricing implications of speculative retail trading. We use portfolios sorted by RTP as well as the Fama-MacBeth (1973) regressions of next month's stock returns on current RTP of stocks. Both approaches show that high-RTP stocks have significantly lower average returns. The annual, risk-adjusted RTP premium (i.e., the difference between the value-weighted portfolios of the top and bottom RTP quintiles) is about -7%. This result is robust to variations in portfolio sorting and weighting methods. It is not limited to particular sample periods. It is stronger among small stocks. Our results do not change materially when we follow the Asparouhova, Bessembinder, and Kalcheva (2010) method to account for the impact of potential microstructure-induced noise.

Importantly, the negative RTP premium is exclusively due to the underperformance of high-RTP stocks and not due to the overperformance of low-RTP stocks. High-RTP stocks have a high contemporaneous return but significant negative alpha the next month. Thus, high-RTP stocks tend to be overpriced. It is consistent with the pricing impact of noise traders for high-RTP stocks, because these stocks not only are dominated by retail investors, they also face high limits to arbitrage. High-RTP stocks tend to have very low market capitalization, low price, high IVOL, low institutional ownership, and low analyst coverage (ANCOV).

Our results support several recent behavioral theories that provide reasons why high-RTP stocks can be overpriced. For example, Scheinkman and Xiong (2003) show that stocks are overpriced when the level of speculative trading is high because of the high resale option value due to large disagreement among investors. Barberis and Huang (2008) show that stocks with high skewness should earn low average returns, because investors with cumulative prospect theory utility overweight tiny probabilities of large gains. Barberis and Xiong (2012) predict a low average return of stocks held and traded primarily by individual investors who are influenced by realization utility, such as highly volatile stocks.

Results from additional tests further support that the negative RTP premium reflects speculative retail investors' willingness to hold and trade stocks with strong lottery features. For example, the negative RTP premium is stronger among stocks that have lottery features or are located in regions in which people exhibit a stronger propensity to gamble.[1] Furthermore, we show that the negative volatility-return relation identified in the previous literature is stronger among stocks whose trading is dominated by retail investors.[2] The pricing effects of speculative retail trading generalize beyond the volatility-return relation. We find that lottery-type stocks (i.e., stocks with low prices, high IVOL, and high idiosyncratic skewness (ISKEW)) earn low average returns, and this negative lottery stock premium is stronger for high-RTP stocks.

Our results extend the recent literature on retail investors. In particular, Kumar (2009) examines the gambling preferences of retail investors and identifies investor attributes that are more strongly associated with people's propensity to gamble. Building upon those earlier findings, we identify a proxy for retail trading for a longer time period and use it to study the asset pricing implications of speculative retail clienteles. Our asset pricing results add to the growing evidence on the importance of retail investors in the return-generating process

[1] Following Kumar, Page, and Spalt (2011), we use the ratio of Catholic and Protestant adherents in a county (CPRATIO) as a proxy for people's propensity to gamble.

[2] Ang, Hodrick, Xing, and Zhang (AHXZ) (2006), (2009) first documented that high-IVOL stocks earn low average returns.

(e.g., Kumar and Lee (2006), Barber, Odean, and Zhu (2009), Dorn, Huberman, and Sengmueller (2008), Hvidkjaer (2008), and Kaniel, Saar, and Titman (2008)). In broader terms, our results highlight the usefulness of a habitat-based approach for studying asset prices.

The rest of the paper is organized as follows: In Section II, we describe our data sources and define the retail trading proxy RTP. In Section III, using this proxy, we identify the stocks that speculative retail investors find attractive and verify that RTP captures speculative retail trading. In Section IV, we examine the asset pricing implications of speculative retail trading. Section V concludes the paper.

II. Retail Trading Proxy

A. Data Sources

We use data from several sources to test our hypotheses. Our 1st main data set contains stock-level measures of retail trading from the ISSM and the TAQ databases for the 1983–2000 period. We use small trades (trade size $\leq$ \$5,000) to proxy for retail trades, where like Barber et al. (2009), we use the ISSM/TAQ data only until the year 2000. The introduction of decimalized trading in 2001 and order splitting by institutions due to lower trading costs imply that trade size would not be an effective proxy for retail trading after the year 2000. To further ensure that the small trades reflect retail trading, we compare the ISSM/TAQ data with the portfolio holdings and trades of a sample of individual investors from a large U.S. discount brokerage house for the 1991–1996 period.[3]

We use investors' demographic characteristics, including age, income, location (zip code), occupation, marital status, gender, etc. The demographic characteristics of investors in the brokerage sample are measured a few months after the end of the sample period (June 1997) and are provided by Infobase, Inc. We obtain the county-level geographical variation in the religious composition across the United States. We collect data on religious adherence using the "Churches and Church Membership" files from the American Religion Data Archive. The ratio of the proportion of Catholics and the proportion of Protestants in a county has been shown to be significantly related to the propensity of its residents to speculate and gamble (Kumar et al. (2011)).

We also gather data from various standard sources. The daily and monthly split-adjusted stock returns, stock prices, and shares outstanding for all traded firms are from the Center for Research on Security Prices (CRSP). Following a common practice, we restrict the sample to firms with CRSP share codes 10 and 11. Firms' book value of equity and book value of debt are obtained from Compustat. We obtain the monthly Fama-French (1993) factor returns and monthly risk-free rates from Kenneth French's data library.[4] Both the daily and the

[3]See Barber and Odean (2000) for additional details about the retail investor data set and Barber et al. (2009) or Hvidkjaer (2008) for additional details about the ISSM/TAQ data sets, including the procedure for identifying small trades.

[4]The data library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

monthly data range from Jan. 1983 to Dec. 2000. Last, we obtain stocks' institutional ownership using Thomson Reuters' 13(f) data and analyst coverage information from Thomson Reuters' Institutional Brokers' Estimate System (IBES) data set.

B. The RTP Measure

We compute each stock's RTP as the ratio of the total month-t buy- and sell-initiated small-trades (trade size below $5,000) dollar volume and the total stock trading dollar volume in the same month. We obtain the RTP measure for each stock at the end of each month. Ideally, we would like to observe the trades of all retail investors but, unfortunately, such detailed retail trading data are not available in the United States for an extended time period. Therefore, we use the buy- and sell-initiated small trades as a proxy for retail trading. Several recent studies have used the same $5,000 trade size cutoff and adopted a similar identification strategy to identify retail trades (e.g., Lee and Radhakrishna (2000), Battalio and Mendenhall (2005), Malmendier and Shanthikumar (2007), Barber et al. (2009), and Hvidkjaer (2008)).[5]

To ensure that our RTP variable reflects the behavior of retail investors, we compare RTP with actual retail holdings and trading data from the discount brokerage house. Figure 1 shows the excess portfolio weight and the excess trading weight for RTP-sorted portfolios. The excess weight reflects the difference between the actual portfolio weight in the aggregate retail investors' portfolio based on the brokerage data and the market portfolio constructed using all CRSP stocks. The sample averages of the excess weights are shown in the figure. The excess trading weight is defined in an analogous manner using the total trading volume (sum of buy and sell volumes) measure. Figure 1 shows that both the portfolio and trading weights in the brokerage sample increase with the level of RTP. Retail investors in the discount brokerage house overweight considerably and trade more stocks that have higher RTP.

In an unreported table, we estimate Fama-MacBeth (1973) and cross-sectional regressions with RTP as the dependent variable. We find that both the portfolio weight and the trading weight obtained using the actual holdings and trades of retail investors at the discount brokerage house are strongly and positively correlated with the RTP measure. Together, these findings suggest that our RTP measure captures the preferences and trading behavior of retail investors reasonably well.

C. Characteristics of RTP-Sorted Portfolios

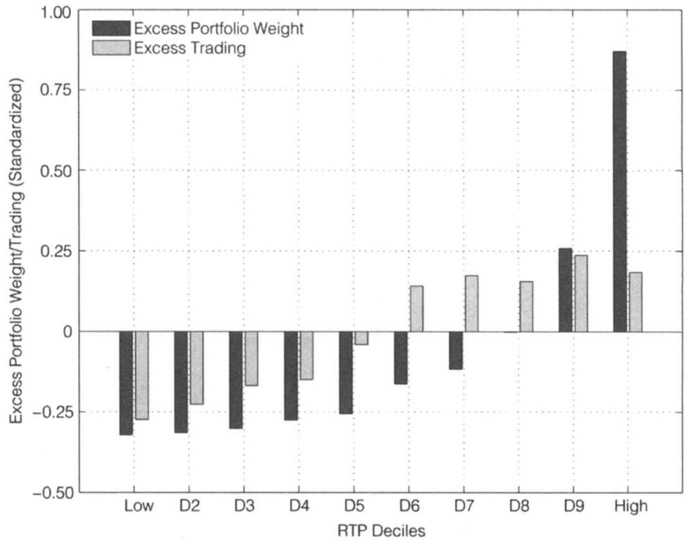
To further examine the ability of the RTP measure to capture retail behavior and to gain insights into the stock preferences of retail investors, each month we sort stocks into deciles based on their RTP. Table 1 reports the mean stock

[5]Lee and Radhakrishna (2000) show that the $5,000 trade size cutoff can effectively identify trades initiated by retail investors. Barber et al. (2009) report that the time-series correlations between trading measures obtained using the small-trades data from ISSM/TAQ and those computed directly using individual investor trades at 2 different brokerage houses are high (around 0.50).

FIGURE 1

Trade Size and Retail Trading

Figure 1 shows the average portfolio and retail trading weights in the brokerage data, conditional upon the level of retail trading proportion (RTP) of the stock. The RTP measure is defined as the ratio of the total buy- and sell-initiated small-trades (trade size below $5,000) dollar volume and the total market dollar trading volume. The small-trades data are from Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases, where small trades are used as a proxy for retail trades. The excess weight is defined as the difference between actual and expected weights. The expected decile weight is the total weight of the decile stocks in the aggregate market portfolio. The market portfolio is defined by including all stocks available in the CRSP database. The actual decile weight in a certain month t is defined as the month-t weight of decile stocks in the aggregate portfolio of individual investors. The aggregate individual investor portfolio is obtained by combining the portfolios of all investors. The weights are standardized (mean is set to 0 and the standard deviation is 1) to facilitate comparisons between the 2 weight measures. The averages of those weights for the Jan. 1991–Nov. 1996 sample period are shown in the figure.



characteristics of RTP-sorted portfolios for the 1983–2000 time period. There is very little retail trading in the bottom 5 RTP deciles. The RTP is only 0.74% on average for the lowest-RTP decile. Even for the 8th decile, the RTP is 20.57%. The majority of retail trading is concentrated in stocks ranked in the top 2 deciles by RTP. The RTP is 63.75% on average for the top decile.

Consistent with the idea that RTP captures retail preferences, we find that a stock's institutional ownership, market capitalization and stock price all decrease monotonically with RTP. Stocks in the top 3 RTP deciles all have average price below $10 and average market value below $100 million dollars. Together, the top 5 RTP deciles represent less than 10% of the total stock market capitalization. The stocks in the highest-RTP decile have an average institutional ownership of only 3.01%, with 57.72% of stocks having IO below 5%. In contrast, the average IO for the lowest-RTP decile is 50.78%, and only 3.19% stocks in this decile have IO below 5%.

Although the level of IO declines monotonically across the RTP deciles, the magnitude of the correlation between RTP and IO is not very high. The average correlation between RTP and $1-\text{IO}$ is 0.193 when we compute the cross-sectional correlation each quarter and then take the average across all quarters. This correlation is even lower (only 0.049) when we first compute time-series correlations

TABLE 1

Small-Trades Volume and Stock Characteristics

Table 1 reports the mean stock characteristics of retail trading proportion (RTP) sorted decile portfolios. The RTP is defined as the ratio of the total monthly buy- and sell-initiated small-trades (trade size below $5,000) dollar volume and the total market dollar trading volume during the same month. Small trades are used as a proxy for retail trades. The small-trades data are from Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases. The following stock characteristic measures are reported: idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), stock price, lottery stock index (LOTT), firm size (in billion dollars), book-to-market (BM) ratio, past 12-month return (12mRet), contemporaneous monthly stock return (RET), institutional ownership (IO), proportion of stocks in the portfolio with low (less than 5%) institutional ownership (Low IO), and analyst coverage (ANCOV). The IVOL in month *t* is defined as the standard deviation of the residual from a 4-factor model (the 3 Fama-French (1993) factors and the momentum factor), where daily returns from month *t* are used to estimate the model. ISKEW is defined as the scaled 3rd moment of residuals from a factor model that contains market return over the risk-free rate (RMRF) and $RMRF^2$ as factors. LOTT is defined as the sum of the vigintile assignments according to the IVOL, ISKEW, and stock price measures divided by 60. The "FracMkt" column reports the fraction of the market represented by the RTP decile portfolio. Each decile portfolio contains an average of 410 stocks. The sample period is Jan. 1983–Dec. 2000. The institutional holdings data are from Thomson Reuters. The salient numbers are shown in bold.

RTP Decile	Mean RTP	FracMkt	IVOL	ISKEW	Price	LOTT	Size ($b)	BM	12mRet	RET	IO	Low IO	ANCOV
Low	**0.74%**	**39.26%**	**11.66%**	**0.386**	**$46.19**	**0.269**	**$3.145**	**0.592**	**31.62%**	**0.47%**	**50.78%**	**3.19%**	**11.59**
D2	1.66%	24.56%	12.03%	0.398	$27.16	0.296	$1.556	0.639	27.71%	0.43%	44.56%	3.23%	9.57
D3	2.70%	15.59%	13.07%	0.402	$23.20	0.332	$0.956	0.675	26.14%	0.91%	38.65%	4.41%	7.29
D4	4.09%	9.06%	13.89%	0.414	$19.67	0.369	$0.546	0.719	23.54%	1.03%	32.79%	6.59%	5.54
D5	6.04%	5.04%	15.12%	0.437	$16.83	0.408	$0.299	0.739	20.94%	1.26%	27.74%	9.12%	4.18
D6	8.86%	2.95%	16.47%	0.493	$13.98	0.453	$0.174	0.765	17.10%	1.19%	23.15%	13.09%	3.08
D7	13.27%	1.76%	18.54%	0.560	$11.20	0.508	$0.103	0.785	13.13%	1.87%	18.93%	18.52%	2.14
D8	20.57%	0.98%	22.20%	0.610	$8.28	0.581	$0.058	0.783	7.86%	2.04%	14.83%	26.54%	1.37
D9	33.64%	0.56%	28.50%	0.678	$5.44	0.671	$0.032	0.729	1.62%	2.22%	10.92%	38.14%	0.79
High	**63.75%**	**0.24%**	**41.51%**	**0.745**	**$2.97**	**0.776**	**$0.014**	**0.871**	**−11.46%**	**2.12%**	**3.01%**	**57.72%**	**0.30**

between RTP and 1−IO for each stock and then average the correlations over all stocks. These comparisons indicate that RTP is not merely some linear transformation of 1−IO.[6]

Table 1 also shows that the average IVOL and ISKEW increase, while stock price decreases monotonically across the RTP decile portfolios.[7] The stocks in the highest-RTP decile have an average IVOL of 41.51%, while those in the lowest-RTP decile have an average IVOL of only 11.66%. Similarly, the average ISKEW for the highest-RTP decile portfolio is 0.745, which is almost twice the average ISKEW of 0.386 for the lowest-RTP decile portfolio. These estimates, along with the monotonically increasing pattern in the lottery stock index (LOTT) column, indicate that the levels of retail trading are higher among stocks that are usually perceived as speculative stocks.

Examining other stock characteristics of RTP-sorted portfolios, we find that stocks with a high fraction of retail trading have higher book-to-market (BM) ratios, lower ANCOV, and lower past returns. In fact, the highest-RTP decile stocks earn an average of −11.46% over the past 12 months, while the lowest-RTP decile stocks earn an average of 31.62%. Furthermore, the contemporaneous stock

[6]See Hvidkjaer (2008) for additional comparisons between the ISSM/TAQ small-trades data and the 13(f) institutional holdings data. The key conclusion from his analysis is also that the ISSM/TAQ small-trades data do not merely proxy for 1−IO.

[7]Following AHXZ (2006), we measure a stock's IVOL in a given month-*t* as the standard deviation of the residual obtained by fitting a 4-factor model Fama-French (1993) 3 factors plus a momentum factor to its daily returns during month *t*. ISKEW is computed using the Harvey and Siddique (2000) method. It is defined as the scaled measure of the 3rd moment of the residual obtained by fitting a 2-factor (RMRF and $RMRF^2$) model to daily returns from the previous 6 months, where RMRF is the market return, excess over the risk-free rate.

returns increase with RTP. In particular, the same-month returns of the top 2 RTP deciles are both over 2% on average.

III. RTP and Speculative Retail Trading

In this section, we conduct additional tests to show that the RTP measure captures speculative trading activities of retail investors. We also show that retail trading levels are high for stocks that offer greater opportunities for experiencing realization utility (Barberis and Xiong (2012)). The recent behavioral finance literature has already demonstrated that retail investors overweight stocks with speculative or "lottery" features, including IVOL (e.g., Kumar (2009)). We confirm this finding using a data set that covers a longer time period and a larger segment of the market. We also present new results, which indicate that speculative stocks attract risk-seeking, realization utility investors.

A. Speculation-Based Retail Clienteles

To begin, we conduct several tests to examine whether retail investors overweight speculative stocks in their portfolios and exhibit a greater propensity to trade those stocks. Each month, we form portfolios sorted on IVOL and LOTT, which is a composite measure that captures the degree of speculative features in a stock. LOTT is defined as the sum of the vigintile assignments according to the IVOL, ISKEW, and stock price measures divided by 60. The LOTT measure is motivated by Kumar (2009), who shows that investors with a gambling mind-set find stocks with high volatility, high skewness, and low prices more attractive.

We also compute the weights of those portfolios in the market portfolio constructed using all CRSP stocks. The sample period averages of those monthly expected weights (assuming retail investors in aggregate hold the market portfolio) are reported in column 1 of Table 2. In columns 2 and 3, we report the actual weights allocated to IVOL (Panel A) and LOTT (Panel B) portfolios by brokerage investors in their portfolio holdings and trading activities. The trading weight is the ratio of the trading volume of stocks in an IVOL or LOTT portfolio to the total volume of all trades by brokerage investors. In column 4, we obtain trading weights using the small-trades data from ISSM/TAQ. In columns 5–7, we report the excess weights measured as the actual weights in columns 2–4 minus the expected market weights in column 1.

The IVOL and LOTT sorting results reported in Panels A and B of Table 2, respectively, indicate that retail investors exhibit a greater propensity to hold and trade stocks with speculative features. For example, using the end-of-month portfolio holdings of brokerage investors, we find that the expected weight in the lowest-LOTT decile portfolio is 61.43%, while the actual portfolio weight allocated to this portfolio is only 34.19%. In contrast, the expected weight in the highest-LOTT decile portfolio is only 0.17%, but the actual portfolio weight allocated to this portfolio is 4.56%. As a consequence, retail investors underweight the lowest-LOTT decile portfolio by 27.25% and overweight the highest-IVOL decile portfolio by 4.39% (see column 5 of Panel B). The IVOL sorting results reported in Panel A reveal a very similar pattern.

TABLE 2

Speculative Stock Characteristics and Retail Preferences: Sorting Results

Table 2 reports the portfolio holdings and trading levels of retail investors in idiosyncratic volatility (IVOL) and lottery stock index (LOTT) sorted portfolios. The LOTT is defined as the sum of the vigintile assignments according to the IVOL, ISKEW, and stock price measures divided by 60. The IVOL in month t is defined as the standard deviation of the residual from a 4-factor model (the 3 Fama-French (1993) factors and the momentum factor), where daily returns from month t are used to estimate the model. Idiosyncratic skewness is defined as the scaled 3rd moment of residuals from a factor model that contains market return over the risk-free rate (RMRF) and RMRF^2 as factors. IVOL and LOTT deciles are constructed each month and, for each of these deciles, we compute the percentage weights of retail holdings and trading. The sample period averages of those weights are reported in the table. Three different weights are reported: expected weights, actual weights, and excess weights (defined as actual weights − expected weights). The expected decile weight is the total weight of the decile stocks in the aggregate market portfolio. The market portfolio is defined by including all stocks available in the CRSP database with share codes 10 and 11. The actual decile weight in a certain month t is defined as the month-t weight of decile stocks in the aggregate portfolio of individual investors at a large U.S. discount brokerage house. The aggregate individual investor portfolio is obtained by combining the portfolios of all investors. In column 1, we report the expected weights. Column 2 contains the actual portfolio weights based on the stock holdings of all investors in the brokerage sample. Column 3 contains the actual weights based on the stock trades of all investors in the brokerage sample. In column 4, we use the small trades (trade size below $5,000) from the Institute for the Study of Security Markets (ISSM) and the Trade and Quote (TAQ) databases to proxy for retail trading. Columns 5–7 report the difference between columns 2–4 and 1, respectively. The sample period is Jan. 1991–Nov. 1996. The salient numbers are shown in bold.

	Expected Weight		Actual Weight			Excess Weight	
	CRSP	Brok:Pos	Brok:Trd	TAQ/ISSM	Brok:Pos	Brok:Trd	TAQ/ISSM
Sort	1	2	3	4	5	6	7
Panel A. IVOL							
Low	**40.66**	**22.15**	**15.82**	**16.01**	**−18.50**	**−24.84**	**−24.65**
D2	26.68	16.68	15.05	15.61	−10.00	−11.63	−11.07
D3	13.10	10.65	12.18	11.18	−2.45	−0.92	−1.92
D4	8.09	9.27	12.04	10.41	1.17	3.95	2.32
D5	5.10	9.61	13.22	11.67	4.52	8.13	6.57
D6	2.83	7.85	11.19	10.29	5.02	8.37	7.47
D7	1.64	6.99	9.06	9.25	5.36	7.42	7.61
D8	1.09	6.83	6.47	7.76	5.74	5.38	6.67
D9	0.56	5.34	3.04	4.69	4.78	2.48	4.13
High	**0.27**	**4.63**	**1.92**	**3.13**	**4.37**	**1.66**	**2.87**
Panel B. LOTT							
Low	**61.43**	**34.19**	**31.48**	**24.37**	**−27.25**	**−29.96**	**−37.07**
D2	18.31	15.58	18.77	16.99	−2.73	0.46	−1.32
D3	8.48	10.10	13.55	12.47	1.62	5.08	4.00
D4	4.62	7.57	10.77	10.29	2.95	6.16	5.67
D5	2.92	6.48	8.65	8.81	3.56	5.73	5.89
D6	1.76	5.73	6.23	7.70	3.97	4.47	5.94
D7	1.16	5.52	4.51	6.48	4.36	3.35	5.33
D8	0.74	5.21	3.26	5.68	4.47	2.52	4.94
D9	0.42	5.07	1.99	4.57	4.66	1.57	4.15
High	**0.17**	**4.56**	**0.78**	**2.65**	**4.39**	**0.61**	**2.48**

When the weights are computed using trades rather than the end-of-month portfolio holdings, we still find that retail investors overweight stocks with strong lottery features (see column 6). For example, the actual weight in LOTT decile portfolio 8 is more than 4 times (= 3.26%) the expected weight of 0.74%. These trading weight estimates indicate that retail investors not only hold a greater proportion of highly speculative stocks; they also trade them more actively. The excess trading weights from the brokerage data and the ISSM/TAQ data portray a similar picture (compare columns 6 and 7). Overall, these results indicate that speculative stocks seem to be the preferred habitat of retail investors.

We quantify the stock preferences of retail investors more accurately by estimating multivariate regressions of a stock's RTP on various stock characteristics. The results reported in column 1 of Table 3 indicate that, consistent with our

TABLE 3

Stock Preferences of Retail Investors: Fama-MacBeth Regression Estimates

Table 3 reports the Fama-MacBeth (1973) regression estimates, where the dependent variable is a measure of retail or institutional stock preference. In columns 1–4, the dependent variable is the retail trading proportion (RTP) measure. It is defined as the ratio of the total buy- and sell-initiated small-trades dollar volume and the total market dollar trading volume. The small-trades data are from Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases, where small trades are used as a proxy for retail trades. In column 5, the dependent variable is the excess weight assigned to a stock in the aggregate institutional portfolio. The excess portfolio weight allocated to stock i in quarter t is defined as: $EW_{ipt} = 100 \times (w_{ipt} - w_{imt})/w_{imt}$, where, w_{ipt} is the actual weight assigned to stock i in portfolio p in quarter t, and w_{imt} is the weight of stock i in the aggregate market portfolio in quarter t. All independent variables are predetermined and measured with 1 lag relative to the dependent variable. The main independent variables are: i) idiosyncratic volatility (IVOL), which is the standard deviation of the residual from a 4-factor model (the 3 Fama-French (1993) factors and the momentum factor) to the stock returns time series; ii) idiosyncratic skewness (ISKEW), which is defined as the scaled measure of the 3rd moment of the residual obtained by fitting a 2-factor (RMRF and RMRF^2) model to the daily returns from the previous 6 months; and iii) stock price. We also define interaction terms using these 3 measures, where "high" refers to the top 3 deciles and "low" refers to the lowest 3 deciles. A dividend-paying dummy variable (set to 1 if the stock pays a dividend at least once during the previous 1 year) and a NASDAQ dummy variable are also used as potential indicators of speculative characteristics. Additionally, the following control variables are employed: i) Catholic-Protestant ratio (CPRATIO), which is the ratio of the number of Protestant and Catholic adherents in the county in which a firm is located; ii) systematic skewness (the coefficient of RMRF^2 in the 2-factor regression to estimate ISKEW); iii) market beta; iv) firm size; v) book-to-market (BM) ratio; vi) past 12-month stock return; and vii) monthly volume turnover, which is the ratio of the number of shares traded in a month and the number of shares outstanding. We use the Pontiff (1996) methodology to correct Fama-MacBeth standard errors for potential serial correlation. The t-statistics, obtained using the corrected standard errors, are reported in parentheses below the estimates. To ensure that extreme values are not affecting the results, we winsorize all variables at their 0.5 and 99.5 percentile levels. All independent variables except the dummy variables have been standardized (mean is set to 0 and standard deviation is 1) so that the coefficient estimates can be directly compared within and across specifications. The sample period is Jan. 1983–Dec. 2000. The salient numbers are shown in bold.

	Dependent Variable: Monthly RTP of a Stock; Quarterly EW of a Stock in the Institutional Portfolio				
	RTP × 100				EW
Variable	1	2	3	4	5
Intercept	3.706	3.612	3.559	3.440	0.036
	(13.02)	(13.12)	(13.57)	(13.82)	(4.78)
IVOL	**2.295**	**1.996**	**1.699**	**1.681**	**−0.053**
	(8.57)	(7.10)	(7.78)	(7.29)	(−5.70)
ISKEW	**0.366**	**0.211**	**0.206**	**0.201**	**−0.024**
	(4.25)	(3.55)	(3.15)	(3.34)	(−2.54)
log(Stock Price)	**−0.810**	**−0.766**	**−0.878**	**−0.819**	**0.338**
	(−11.50)	(−12.33)	(−11.24)	(−8.60)	(10.50)
Dividend-Paying dummy	−0.025	−0.027	0.004	−0.066	0.117
	(−2.60)	(−2.10)	(0.34)	(−3.01)	(7.74)
NASDAQ dummy	0.036	0.039	−0.006	0.011	−0.096
	(1.53)	(1.70)	(−0.26)	(1.11)	(−6.23)
High IVOL × High ISKEW		**0.175**	**0.158**	**0.147**	**−0.044**
		(5.20)	(4.07)	(3.88)	(−3.14)
High IVOL × Low Price		**0.212**	**0.274**	**0.268**	**−0.060**
		(5.22)	(7.33)	(6.80)	(−4.66)
High ISKEW × Low Price		**0.142**	**0.166**	**0.162**	**−0.038**
		(3.50)	(3.80)	(3.54)	(−3.67)
CPRATIO			**0.299**	**0.289**	0.031
			(3.54)	(3.01)	(0.74)
Systematic Skewness			0.020	0.025	0.022
			(0.70)	(0.81)	(2.17)
Market Beta			0.099	0.149	0.101
			(1.13)	(1.80)	(7.08)
log(Firm Size)			−0.098	−0.111	0.190
			(−5.58)	(−5.22)	(6.68)
BM ratio			0.155	0.160	0.013
			(5.57)	(3.68)	(2.04)
Past 12-Month Stock Return			−0.154	−0.118	0.084
			(−2.32)	(−2.01)	(5.01)
Monthly Turnover			0.622	0.512	−0.026
			(5.88)	(4.52)	(−3.00)
Lagged RTP	4.830	4.870	4.677		
	(13.01)	(12.64)	(10.44)		
Avg. no. of obs.	3,795	3,795	3,748	3,756	4,596
Avg. adj. R^2	0.451	0.486	0.524	0.194	0.328

univariate sorting results, all else being equal, retail investors trade stocks with high IVOL more actively. RTP levels are also higher for stocks that are likely to be viewed as speculative instruments, such as stocks with low prices, high ISKEW levels, and nondividend-paying status.

To further establish that RTP captures the speculative preferences of retail investors, we introduce several interaction terms in the RTP regression specification using price, IVOL, and ISKEW variables. The regression estimates in column 2 of Table 3 show that High IVOL × Low Price and High IVOL × High ISKEW interaction terms have significantly positive coefficient estimates. Thus, stocks with higher IVOL have even higher RTP if they are both low priced and have high ISKEW. Similarly, the significantly positive estimate of the High ISKEW × Low Price interaction dummy variable indicates that high-skewness stocks have higher levels of RTP if they also have low prices.

We also test whether the RTP is higher for firms located in regions in which people exhibit a stronger propensity to gamble. This test is motivated by the prior evidence, which indicates that investors disproportionately hold and trade local stocks and that gambling propensities across different domains are positively correlated. Following Kumar et al. (2011), we use the ratio of Catholic and Protestant adherents in a county (CPRATIO) as a proxy for people's propensity to gamble.[8] Using this gambling proxy, we find that the RTP levels are higher in regions with a higher CPRATIO (see columns 3 and 4 of Table 3). This evidence further supports our conjecture that RTP reflects the speculative behavior of retail investors.[9]

For comparison with institutional stock preferences, column 5 of Table 3 reports the estimates from a regression in which the excess portfolio weight of the institutions in each stock is the dependent variable.[10] Many institutions are governed by prudent man rules, which require institutional investors with fiduciary obligations to invest in "high quality" stocks (e.g., Badrinath, Gay, and Kale (1989), Del Guercio (1996)). Thus, institutions are likely to shun speculative stocks. Supporting this view, we find that institutions as a group underweight speculative stocks. The coefficient estimate of IVOL and ISKEW as well as the interaction terms between the 3 dummy variables High IVOL, High ISKEW, and Low Price are all significantly negative. These results demonstrate that, unlike retail investors, institutions typically avoid stocks with speculative features.

[8]This identification strategy is motivated by the observation that gambling attitudes are strongly determined by one's religious background. In particular, the Protestant and Catholic churches have very distinct views on gambling. The Roman Catholic church maintains a tolerant attitude toward moderate levels of gambling and is less disapproving of gambling activities, while a strong moral opposition to gambling and lotteries has been an integral part of the Protestant movement since its inception. Kumar et al. (2011) show that the predominant religion of a region could influence local cultural values and norms and thereby affect the financial and economic decisions of individuals located in that region, even if they do not personally adhere to the local faith.

[9]We exclude lagged RTP from the specification in column 4 of Table 3 to show that our results are not very sensitive to the choice of the regression specification.

[10]The excess portfolio weight allocated to stock i in quarter t is defined as: $EW_{ipt} = 100 \times (w_{ipt} - w_{imt})/w_{imt}$, where, w_{ipt} is the actual weight assigned to stock i in portfolio p in quarter t and w_{imt} is the weight of stock i in the market portfolio in quarter t. The aggregate institutional portfolio is defined by combining the portfolio holdings of all 13(f) institutions.

B. Additional Evidence of Speculative Retail Clienteles

To further test the claim that RTP captures the speculative behavior of retail investors, we examine the characteristics of the retail investor clientele of high-RTP stocks. We conjecture that the characteristics of retail clienteles of high-RTP stocks would be similar to the characteristics of investors who are more likely to engage in speculative or gambling-motivated trading (e.g., younger, male, less educated, and low-income investors), as documented in Kumar (2009).

We test this hypothesis using the retail investors' holdings from a large U.S. discount brokerage house for the 1991–1996 period and their demographic characteristics. For each stock, we measure the average characteristics of brokerage investors who trade the stock during the 6-year sample period. Using these clientele characteristics, we estimate a cross-sectional regression in which the sample-period average RTP for a stock is the dependent variable, and the average clientele characteristics of the stock are the independent variables. The results are reported in Table 4. In column 1, we report estimates from a specification that only includes characteristics that are available in the brokerage data, and in column 2, we consider additional characteristics defined using measures associated with investors' location.

We find that stocks with high levels of RTP have younger clienteles with lower income, lower education levels, and nonprofessional occupations. Those stocks also have a greater proportion of male and single investors. Retail investors of high-RTP stocks tend to hold less-diversified portfolios. Moreover, the RTP is high for stocks that are held by urban investors and those who reside in areas with higher per capita lottery expenditures. Both of these geographical characteristics are associated with a greater propensity to speculate and gamble. These demographic characteristics, along with the religious and racial/ethnic characteristics of high-RTP stocks, are very similar to the characteristics of investors who are more attracted toward speculative and lottery-type stocks (Kumar (2009)). These results further support that RTP is a good proxy for retail speculation.

When we consider an alternative measure of retail trading that captures the direction of trading (i.e., the buy-sell imbalance (BSI)), we find completely different results (see column 3 of Table 4).[11] Stocks with higher levels of BSI do not have clientele characteristics that are similar to the characteristics of investors who find speculative stocks attractive. The BSI regression estimates indicate that RTP is a more appropriate proxy than BSI for retail speculation. This evidence also indicates that speculative investors are not merely accumulating the shares of the stocks they like. Rather, they actively buy as well as sell those stocks.

For robustness, in columns 4 and 5 of Table 4, we report estimates using extended specifications that include various stock characteristics used in Table 3 as additional control variables. The results from these extended specifications are similar to the baseline results reported in columns 1–3.

[11]Like RTP, BSI is computed using the ISSM/TAQ data, where we use small trades to proxy for retail trades. BSI is defined as $(B-S)/(B+S)$, where B is the total monthly buy-initiated small-trades volume and S is the total monthly sell-initiated small-trades volume.

TABLE 4

Investor Characteristics and Retail Trading: Cross-Sectional Regression Estimates

Table 4 reports cross-sectional regression estimates, where the dependent variable is the average retail trading proportion (RTP) or the buy-sell imbalance (BSI) of a stock measured over the 1991–1996 brokerage sample period. RTP is defined as the ratio of the total buy- and sell-initiated small-trades dollar volume and the total market dollar trading volume. Small trades are used as a proxy for retail trades. The small-trades data are from Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases. BSI is defined as the ratio of small-trades BSI (buy-initiated small-trades volume − sell-initiated small-trades volume) and total small-trades volume. The main independent variables are the following mean characteristics of the retail investor clientele that trades the stock: Age, Annual Income, Education, Professional Occupation, Gender (Proportion Male), Marital Status (Proportion Married), Proportion Catholic, Proportion African-American, Proportion Hispanic, Proportion Foreign Born, Proportion Urban (located within 100 miles of the top 25 U.S. metropolitan regions), Average State-Level Lottery Sales, and Portfolio Concentration (1 − normalized variance, which is defined as portfolio variance divided by the average variance of stocks in the portfolio). The clientele characteristic is the equal-weighted average characteristic of a sample of retail investors who trade the stock during the 1991–1996 sample period, where stocks with fewer than 5 trades are excluded from the sample. The data on the portfolio holdings, trading, and demographics of individual investors are from a large U.S. discount brokerage house over the 1991–1996 time period. In specifications 4 and 5, we include the following stock characteristics as additional control variables: firm size, book-to-market ratio, past 12-month stock return, monthly turnover, idiosyncratic volatility (IVOL), market beta, idiosyncratic skewness (ISKEW), systematic skewness, stock price, dividend-paying dummy variable, and NASDAQ dummy variable. The *t*-statistics are reported in parentheses below the estimates. To ensure that extreme values are not affecting the results, we winsorize all variables at their 0.5 and 99.5 percentile levels. All independent variables except the dummy variables have been standardized (mean is set to 0 and standard deviation is 1).

				Additional Controls	
	RTP × 100		BSI × 100	RTP × 100	BSI × 100
Variable	1	2	3	4	5
Intercept	3.371	3.375	−2.267	3.041	−2.251
	(22.12)	(20.56)	(−4.49)	(19.52)	(−4.72)
Age	−0.494	−0.539	0.208	−0.442	0.181
	(−2.41)	(−2.52)	(0.40)	(−2.14)	(0.56)
Income	−1.111	−0.781	0.074	−0.968	0.107
	(−5.33)	(−3.50)	(0.14)	(−3.67)	(0.21)
Professional dummy	−0.466	−0.280	0.918	−0.339	0.873
	(−2.08)	(−1.63)	(1.63)	(−1.82)	(1.70)
Proportion Male	1.749	1.774	−1.299	1.702	−1.005
	(6.23)	(5.93)	(−1.82)	(5.95)	(−1.63)
Proportion Married	−1.264	−1.181	0.002	−1.108	0.006
	(−4.55)	(−4.08)	(0.22)	(−4.01)	(0.26)
Portfolio Concentration	2.277	2.228	−3.054	1.858	−2.896
	(9.96)	(9.39)	(−5.26)	(8.19)	(−5.27)
Education		−1.539	1.853	−1.420	1.828
		(−6.63)	(3.29)	(−6.40)	(3.27)
Proportion Catholic		1.455	1.700	1.518	1.815
		(4.93)	(2.38)	(5.38)	(2.79)
Proportion African-American		0.356	0.077	0.237	0.084
		(1.78)	(0.14)	(1.51)	(0.16)
Proportion Hispanic		0.587	−0.114	0.577	−0.088
		(2.06)	(−0.19)	(1.98)	(−0.61)
Proportion Foreign Born		0.134	0.652	0.133	0.625
		(0.56)	(1.86)	(0.59)	(1.89)
Proportion Urban		0.474	0.937	0.490	0.919
		(2.69)	(1.38)	(2.83)	(1.30)
Average State-Level Lottery Sales		1.113	−1.603	1.171	−2.037
		(5.18)	(−3.05)	(5.71)	(−4.09)
No. of stocks	6,231	5,925	5,925	5,901	5,883
Adj. R^2	0.032	0.059	0.011	0.122	0.106

C. Realization Utility-Induced Retail Clienteles

Another reason why some retail investors may prefer speculative stocks such as high-volatility stocks is suggested by Barberis and Xiong (2012). They propose a model in which investors derive utility just from the act of realizing gains on the stocks they own, and they show that realization utility investors' initial utility is increasing in a stock's volatility. These investors prefer high-volatility stocks because a highly volatile stock offers a greater chance of experiencing a large gain. Barberis and Xiong also predict that more volatile stocks will be traded more frequently.

One implication of Barberis and Xiong (2012) is that investors' propensity to realize gains would be stronger among stocks with higher IVOL. In addition, Barberis and Xiong show that realization utility can lead to the disposition effect. If realization utility matters more to individual investors than to institutional investors, the disposition effect would be stronger among high-RTP stocks.

In Table 5, we use the brokerage data to test Barberis and Xiong's (2012) predictions concerning investors' propensity to realize gains and the disposition effect. We estimate pooled ordinary least squares (OLS) regressions with year fixed effects, where the dependent variable is one of the following measures:

TABLE 5

Stock Characteristics and the Propensity to Sell Winners and Losers: Panel Regression Estimates

Table 5 reports panel regression (pooled OLS with year fixed effects) estimates, where the dependent variable is 1 of the following 3 measures in year t for a given stock: i) proportion of gains realized (PGR) (columns 1–3), ii) proportion of losses realized (PLR) (column 4), and iii) disposition effect (DE) defined as PGR/PLR (column 5). PGR is defined as the ratio of the number of realized "winners" (stock positions where an investor experiences a gain) and the total number of winners (realized + paper). PLR is defined in an analogous manner. To ensure that these measures are less noisy, stocks with fewer than 10 trades during a year are excluded. The main independent variables are retail trading proportion (RTP), idiosyncratic volatility (IVOL), and idiosyncratic skewness (ISKEW). RTP is defined as the ratio of the total buy- and sell-initiated small-trades dollar volume and the total market dollar trading volume. The IVOL measure is the variance of the residual obtained by fitting a 4-factor model (the 3 Fama-French (1993) factors and the momentum factor) to the stock returns time series. ISKEW is defined as the scaled measure of the 3rd moment of the residual obtained by fitting a 2-factor (RMRF and RMRF^2) model to the daily returns from the previous 6 months. RMRF is the market return, excess over the risk-free rate. Both measures are estimated for each stock each month using daily returns data. Additionally, the following control variables are employed: i) monthly volume turnover, which is the ratio of the number of shares traded in a month and the number of shares outstanding; ii) firm age, which is the number of years since the stock first appears in the CRSP database; iii) market beta; iv) firm size; v) book-to-market (BM) ratio; vi) past 12-month stock return; vii) a dividend-paying dummy variable, which is set to 1 if the stock pays dividend at least once during the previous 1 year; viii) institutional ownership in the stock; ix) a NASDAQ dummy variable; x) stock price; xi) bid-ask spread; and xii) analyst coverage (ANCOV), which is defined as the number of analysts covering the stock during the past year. All independent variables are measured during the year $t-1$. To ensure that extreme values are not affecting the results, we winsorize all variables at their 0.5 and 99.5 percentile levels. Both the dependent and the independent variables except the dummy variables have been standardized (mean is set to 0 and standard deviation is 1) so that the coefficient estimates can be directly compared within and across specifications. To account for potential serial and cross correlations in errors, we compute firm and year clustered standard errors. The t-statistics, obtained using the corrected standard errors, are reported in parentheses below the estimates. The salient numbers are shown in bold.

	PGR			PLR	DE
Variable	1	2	3	4	5
RTP	**0.144**		**0.042**	**−0.055**	**0.060**
	(10.18)		(4.34)	(−3.12)	(4.66)
IVOL		**0.224**	**0.187**	**−0.052**	**0.159**
		(15.72)	(12.68)	(−3.44)	(8.35)
ISKEW		**0.150**	**0.130**	**−0.041**	**0.087**
		(10.63)	(9.51)	(−2.51)	(9.01)
Monthly Turnover			0.100	0.088	0.049
			(8.80)	(3.98)	(3.55)
Firm Age			0.011	0.017	−0.008
			(2.60)	(2.45)	(−1.10)
Market Beta			0.027	−0.014	0.019
			(4.41)	(−1.02)	(1.65)
log(Firm Size)			−0.168	−0.101	−0.140
			(−6.66)	(−5.12)	(−4.54)
BM ratio			0.001	−0.020	−0.003
			(0.062)	(−1.32)	(−0.46)

(continued on next page)

TABLE 5 (continued)

Stock Characteristics and the Propensity to Sell Winners and Losers: Panel Regression Estimates

	PGR			PLR	DE
Variable	1	2	3	4	5
Past 12-Month Stock Return			0.035 (2.02)	0.085 (4.78)	−0.042 (−2.50)
Dividend-Paying dummy			−0.009 (−0.48)	−0.008 (−0.44)	−0.004 (−0.14)
NASDAQ dummy			−0.031 (−1.77)	−0.002 (−0.13)	−0.011 (−0.57)
Institutional Ownership			−0.030 (−1.56)	−0.007 (−0.36)	−0.021 (−1.62)
log(Stock Price)			−0.094 (−3.22)	0.017 (0.60)	−0.029 (−2.11)
Bid-Ask Spread			−0.105 (−4.41)	−0.120 (−5.01)	0.055 (3.35)
log(1 + ANCOV)			0.040 (1.60)	0.011 (1.04)	0.039 (1.66)
No. of obs.	13,856	13,856	13,077	13,077	13,077
Adj. R^2	0.028	0.059	0.137	0.053	0.071

i) the proportion of gains realized (PGR), ii) the proportion of losses realized (PLR), and iii) the ratio PGR/PLR. The 3 measures are computed for each stock at the end of each year using the portfolio holdings and trades of all brokerage investors. PGR is defined as the ratio of the number of realized "winners" (stock positions where an investor experiences a gain) and the total number of winners (realized + paper). PLR is defined in an analogous manner. We use PGR−PLR as the measure of the stock-level disposition effect. Additional details on these measures are available in Odean (1998).

The main independent variables of interest are the RTP and the IVOL level of the stock. Several other stock characteristics are employed as control variables, and they are defined in the caption of Table 5. All independent variables are measured during year $t-1$.

Consistent with the empirical predictions of the Barberis and Xiong (2012) model, we find that there is a positive relation between IVOL and PGR (see columns 2 and 3 of Table 5), and the disposition effect is stronger for stocks with higher IVOL (see column 5). We also find that RTP is positively correlated with the propensity to realize gains, and the disposition effect is stronger for high-RTP stocks.

We further verify these results using a portfolio-based approach. We define RTP-sorted decile portfolios and measure the average PGR and the average disposition effect (= PGR−PLR) for those portfolios. The average PGR is 15.32% for the lowest-RTP decile portfolio and 22.66% for the highest-RTP decile portfolio. In addition, the average disposition effect is 5.28% for the lowest-RTP decile portfolio and 10.77% for the highest-RTP decile portfolio.

Overall, the results reported in this section indicate that high-RTP stocks have speculative characteristics and attract the clientele of retail investors who are known to engage in speculative or gambling-motivated trading. High-RTP stocks are more influenced by the activities of risk-seeking "realization utility" investors as modeled in Barberis and Xiong (2012).

IV. Speculative Trading and Asset Prices

In this section, we study the asset pricing implications of retail investors' speculative trading activities as captured by the RTP variable. Previous studies have established both theoretically and empirically that noise trading in general can have a systematic price impact (e.g., DeLong, Shleifer, Summers, and Waldmann (1990), Kumar and Lee (2006), and Barber et al. (2009)). A key element for noise traders to affect stock prices is limits to arbitrage. As we have seen, high-RTP stocks tend to have very low market capitalization, low price, high IVOL, low institutional ownership, and low ANCOV. On one hand, we have shown evidence of speculative, risk-seeking, gambling-motivated trading for high-RTP stocks. On the other hand, due to the specific characteristics of high-RTP stocks, they also face high limits to arbitrage such as high transaction costs and high holding costs. These 2 considerations allow the existence of mispricing for high-RTP stocks.

More specifically, several recent theoretical studies suggest that high-RTP stocks are likely to be overpriced. For example, Scheinkman and Xiong (2003) show that stocks are overpriced when the level of speculative trading is high because of the high resale option value due to large disagreement among investors. Barberis and Huang (2008) show that stocks with high skewness should earn low average returns, because investors with cumulative prospect theory utility overweight tiny probabilities of large gains. Barberis and Xiong (2012) predict low average return of stocks held and traded primarily by individual investors who are influenced by realization utility, such as highly volatile stocks.

Thus, we expect high-RTP stocks to earn low average returns. Furthermore, if the preferences of speculative and realization utility retail investors influence the negative relation between average stock returns and retail trading, then this relation should be stronger (more negative) among stocks with speculative characteristics. We test these 2 hypotheses later.

A. RTP and Average Returns: Sorting Results

We first examine the relation between the level of retail trading and the average stock returns. At the end of each month for the Jan. 1983–Dec. 2000 sample period, we form RTP quintile portfolios and compute their equal- and value-weighted returns over the next month. The sorting results reported in Table 6 indicate a negative RTP-return relation that is statistically and economically significant.

In particular, the lowest-RTP quintile earns a value-weighted mean monthly return of 1.325%, while the highest-RTP quintile earns a monthly return of only 0.573%. The monthly return differential between the 2 extreme value-weighted RTP quintile portfolios (i.e., the RTP premium) is −0.752%, which is economically and statistically significant. The spread between the equal-weighted average returns of high- and low-RTP quintiles is −0.505% per month, which is also

TABLE 6

Risk Exposures and Performance of RTP-Sorted Portfolios

Table 6 reports the characteristics and performance of RTP-sorted portfolios. The quintile portfolios are formed at the end of each month using the monthly RTP break points. The monthly retail trading proportion (RTP) is the ratio of the retail trading volume and the total dollar trading volume in the market, where the retail trading volume is the sum of buy- and sell-initiated small-trades dollar volume in the Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases. Panel A reports the raw performance estimates of RTP-sorted portfolios, including the average monthly returns, characteristic-adjusted returns computed using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology, and factor exposures and alphas under the factor model (the 3 Fama-French (1993) factors (market minus the risk-free rate (RMRF), small-minus-big (SMB), and high-minus-low (HML)) plus the momentum (MOM) factor). The following estimates are reported: equal-weighted (EW), value-weighted (VW), and past gross-return-weighted (GRW) using the Asparouhova et al. (2010) method. Panel B reports the alpha estimates for value-weighted RTP quintile portfolios under the 4-factor model from various robustness tests. In the 1st test, following Asparouhova et al., we weight each observation by the prior period gross return on the same stock to account for potential microstructure biases. Next, we exclude stocks priced below \$5. In the 3rd test, we include the short- and long-term reversal factors in the asset pricing model used to obtain the alpha estimates. In the 4th test, we use the data only from the 1983–1991 period. In the 5th test, we exclude January returns. In the last test, we consider only the set of NYSE stocks that do not have short-sale constraints. Due to data availability, the sample period for this test is 1991–2000. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. Only stocks with CRSP share codes 10 and 11 are included in the analysis. The sample period is Jan. 1983–Dec. 2000. The salient numbers are shown in bold.

Panel A. Full-Sample Estimates

	RTP Quintile					
Measure	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High − Low
Mean monthly return (EW)	1.363	1.309	1.191	1.124	0.858	**−0.505**
Std. dev. EW return	4.682	4.891	4.883	5.263	6.594	3.560
Mean monthly return (VW)	1.325	1.305	1.099	0.771	0.573	**−0.752**
Std. dev. VW return	4.303	4.515	4.810	5.521	7.242	3.350
Mean monthly return (GRW)	1.318	1.299	1.153	0.776	0.685	**−0.633**
Std. dev. GRW return	4.604	4.830	4.823	5.212	6.842	3.131
Char.-adjusted return (VW)	0.042	0.012	−0.039	−0.162	−0.528	**−0.570**
	(0.98)	(0.96)	(−0.42)	(−2.06)	(−3.18)	(−3.23)
Char.-adjusted return (GRW)	0.049	0.028	−0.031	−0.244	−0.489	**−0.538**
	(0.68)	(0.79)	(−0.29)	(−2.15)	(−3.25)	(−3.48)
Alpha	0.055	0.074	0.040	−0.215	−0.550	**−0.605**
	(0.98)	(0.96)	(0.42)	(−2.06)	(−3.18)	(−3.29)
RMRF exposure	1.016	1.000	0.959	0.986	0.969	−0.047
	(33.01)	(22.65)	(20.09)	(19.69)	(13.13)	(−0.62)
SMB exposure	−0.073	0.238	0.569	0.857	1.202	1.275
	(−4.15)	(9.94)	(18.84)	(20.46)	(12.90)	(13.81)
HML exposure	0.065	0.058	0.062	0.089	0.002	−0.063
	(2.89)	(1.91)	(1.62)	(1.68)	(0.02)	(−0.50)
UMD exposure	−0.074	−0.054	−0.161	−0.232	−0.426	−0.352
	(−4.70)	(−2.51)	(−5.97)	(−6.20)	(−5.13)	(−4.03)

Panel B. Alpha Estimates from Robustness Checks

	RTP Quintile					
Sample	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High − Low
GRW returns	0.073	0.082	0.078	−0.226	−0.475	**−0.548**
	(0.43)	(0.98)	(1.13)	(−2.01)	(−2.48)	(−2.93)
Price ≥ \$5	0.043	0.039	0.019	−0.188	−0.482	**−0.525**
	(0.72)	(0.56)	(0.21)	(−1.98)	(−2.99)	(−2.95)
Price ≥ \$5, reversal factors	0.053	0.095	−0.017	−0.197	−0.434	**−0.487**
	(0.89)	(1.27)	(−0.20)	(−2.14)	(−3.07)	(−3.15)
1983–1991 subperiod	0.007	0.012	0.065	−0.167	−0.520	**−0.527**
	(0.09)	(0.13)	(0.72)	(−1.81)	(−2.87)	(−3.07)
Exclude January returns	0.073	0.182	0.064	−0.248	−0.548	**−0.621**
	(1.16)	(2.32)	(0.68)	(−2.41)	(−3.26)	(−4.20)
Exclude nonshortable stocks	0.075	0.040	0.087	−0.272	−0.423	**−0.498**
	(0.37)	(0.42)	(1.01)	(−2.13)	(−2.89)	(−3.09)

significant. The characteristic-adjusted performance estimates and the 4-factor (Fama-French (1993) 3 factors plus a momentum factor) alpha estimates portray a very similar picture. The annualized characteristic- and risk-adjusted RTP premium estimates are both about −7%. All these results remain about the same when we follow the Asparouhova et al. (2010) method to account for potential microstructure noise by using gross returns from the previous period to weight the observations.

Panel B of Table 6 indicates that the negative RTP-average return relation is robust. For example, when we exclude stocks with a price below $5 to ensure that microstructure effects (e.g., large bid-ask spreads) are not driving our results, the top RTP quintile still underperforms the low-RTP quintile on average by a statistically significant 0.525% per month. The negative RTP premium remains significant even when we add the short- and long-term reversal factors in the asset pricing model used to obtain the risk-adjusted performance estimates.

It is useful to note a robust pattern in Table 6. The characteristics- or risk-adjusted mean returns of high-RTP portfolios are negative and statistically significant, while those of the low-RTP portfolios are positive but insignificant. Thus, the negative RTP premium is exclusively due to the underperformance of high-RTP stocks and not due to the overperformance of low-RTP stocks. High-RTP stocks, that is, those whose trading is dominated by retail investors, tend to be overpriced. This fits well with the high contemporaneous return of the high-RTP stocks (see Table 1). It is consistent with the pricing impact of noise traders for high-RTP stocks, because these stocks not only are dominated by retail investors; they also face high limits to arbitrage such as short-sale constraints.

However, our results cannot be completely explained by short-sale constraints. When we consider only the set of NYSE stocks that do not have short-sale constraints, we still find that the top RTP quintile has a significant negative alpha of −0.423% per month (last row of Panel B in Table 6). This is consistent with the implications of equilibrium models such as Barberis and Huang (2008) and Barberis and Xiong (2012) that do not require short-sale constraints. The −0.423% alpha of high-RTP stocks without short-sale constraints is less negative than the −0.55% alpha for the high-RTP stocks in the full sample. This supports the idea that short-sale constraints exacerbate the pricing impact of speculative trading.

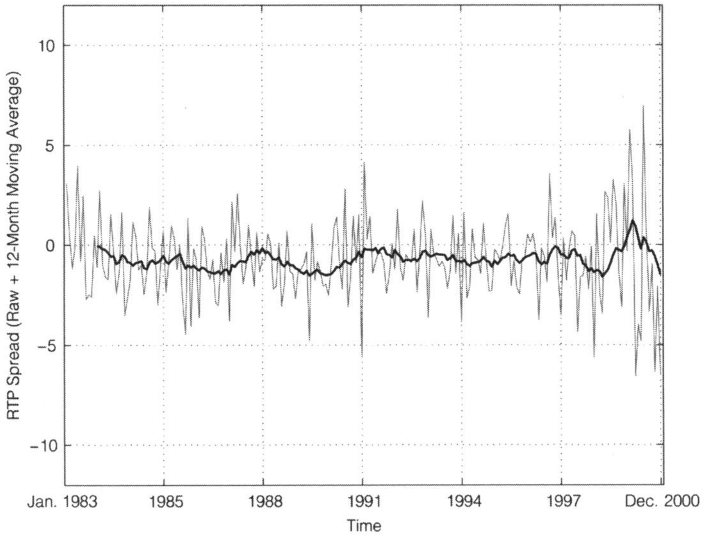
Figure 2 plots the raw monthly return difference between the high (top-quintile) RTP and low (bottom-quintile) RTP portfolios and the 12-month moving average of the monthly return differentials. The high-RTP stocks underperform low-RTP stocks consistently, as the return differential is negative for most of the months during our sample period. While the return differential between the high-RTP and low-RTP stocks becomes larger in magnitude during the NASDAQ bubble period, our results are not driven by this period. The RTP-sorting results reported in Panel B of Table 6 also show that our results are similar when we use the data only from the 1st half of the sample period (1983–1991) or when we exclude January returns. Thus, the profits of RTP-based trading strategies are not limited to a few specific time periods.

Figure 3 illustrates how the return differences between the high-RTP stocks and low-RTP stocks vary with the time gap between portfolio formation and return measurement dates. We find that the return difference (i.e., RTP premium)

FIGURE 2

RTP Premium Time Series

Figure 2 shows the monthly retail trading proportion (RTP) premium, defined as the difference in the value-weighted average monthly returns (in percentage) of high (top quintile) RTP and low (bottom quintile) RTP portfolios. Both the raw and the 12-month backward moving average time series are plotted. The RTP measure is defined as the ratio of the total buy- and sell-initiated small-trades (trade size below $5,000) dollar volume and the total market dollar trading volume. The small-trades data are from Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases, where small trades are used as a proxy for retail trades. RTP portfolios are constructed each month by sorting on RTP estimates in the previous month. In any given month, stocks priced below $5 are excluded from the sample. The sample period is Jan. 1983–Dec. 2000.



becomes smaller as the time gap widens. The RTP premium is significant when the gap between the 2 dates is up to 6 months. It is only weakly significant when we skip about 9 months. The RTP premium estimates eventually lose significance and even switch signs when we skip more than 12 months.

The evidence in Table 7 shows that the RTP premium is larger in magnitude among smaller stocks. Panel A presents the raw returns, while Panel B reports the 4-factor alpha estimates for the value-weighted portfolios.[12] For the top 2 NYSE firm size quintiles, the average monthly RTP premium is statistically weak or insignificant. This evidence adds support to the view that the RTP premium reflects the pricing impact of speculative retail trading, since the concentration of speculative retail trading is higher among smaller stocks.

B. Fama-MacBeth Regression Estimates

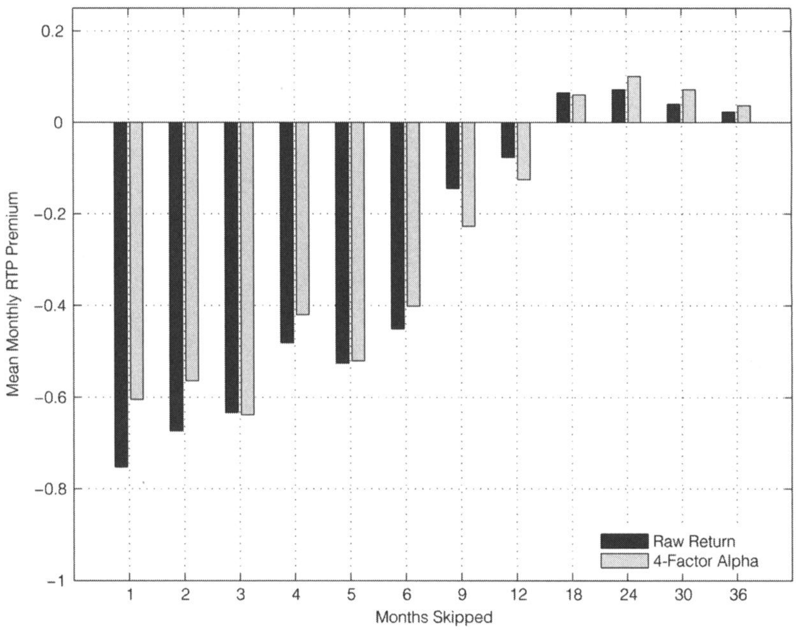
We characterize the influence of retail trading on stock returns more accurately by estimating a series of monthly Fama-MacBeth (1973) regressions, where the regression specification is motivated by AHXZ (2009) and other related

[12]The results are qualitatively very similar when we consider equal-weighted or gross-return-weighted portfolios.

FIGURE 3

Robustness of RTP Premium Estimates

Figure 3 shows the mean monthly retail trading proportion (RTP) premium as the time gap between portfolio formation and return measurement dates varies. The RTP premium is defined as the difference in the value-weighted average monthly returns (in percentage) of high (top quintile) RTP and low (bottom quintile) RTP portfolios. The RTP measure is defined as the ratio of the total buy- and sell-initiated small-trades (trade size below $5,000) dollar volume and the total market dollar trading volume. The small-trades data are from Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases, where small trades are used as a proxy for retail trades. RTP and size portfolios are constructed each month by sorting on RTP and firm size estimates in the previous month, respectively. The sample period is Jan. 1983–Dec. 2000.



studies.[13] The dependent variable in these regressions is the stock return over the next month, while the main independent variable of interest is the stock's RTP in this month. The set of control variables includes various stock characteristics and factor exposures.

The regression estimates are reported in Table 8. Consistent with the sorting results reported in Table 6, we find that stocks with a larger proportion of retail trading in a month earn significantly lower returns in the following month. The RTP variable in column 1 has a significantly negative coefficient (estimate = −0.266, t-statistic = −3.75). This evidence indicates that the RTP-return relation is strongly negative in a multivariate regression setting controlling for many known cross-sectional determinants of expected stock returns.

To examine whether the RTP-return relation varies geographically with people's propensity to gamble, we add a High CPRATIO dummy variable and its interaction with RTP as regressors in specification 2 of Table 8. Recall that CPRATIO is the ratio of Catholic and Protestant adherents in a county. If the

[13]To facilitate comparisons with previous studies, we include factor exposures in all regression specifications. However, our results are very similar and somewhat stronger if we exclude the factor exposures from the regression specifications.

TABLE 7

Performance of RTP and Firm Size Double-Sorted Portfolios

Table 7 reports the mean monthly performance of firm size and retail trading proportion (RTP) sorted portfolios. At the end of each month, we first sort firms based on NYSE size quintiles and then sort firms within each of the NYSE size quintiles into 5 RTP quintiles. RTP and size portfolios are constructed each month by sorting on RTP and firm size estimates in the previous month, respectively. The monthly RTP is the ratio of the retail trading volume and the total dollar trading volume in the market, where the retail trading volume is the sum of buy- and sell-initiated small-trades dollar volume in the Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases. Firm size is defined as the product of number of shares outstanding and end-of-month stock price. Panel A reports the raw performance estimates and Panel B reports the 4-factor model alpha estimates for those value-weighted portfolios. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. Only stocks with CRSP share codes 10 and 11 are included in the analysis. The sample period is Jan. 1983–Dec. 2000. The salient numbers are shown in bold.

		RTP Quintile					
NYSE Size Quintile	All	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High − Low
Panel A. Mean Monthly Returns							
All		1.325	1.305	1.099	0.771	0.573	**−0.752**
							(−3.88)
Q1 (low)	1.051	1.273	1.259	1.024	0.669	0.221	**−1.052**
							(−4.01)
Q2	1.182	1.281	1.334	1.042	0.732	0.310	**−0.971**
							(−3.77)
Q3	1.234	1.312	1.242	1.106	0.805	0.679	**−0.633**
							(−2.82)
Q4	1.317	1.345	1.132	1.122	1.025	0.990	**−0.355**
							(−2.12)
Q5 (high)	1.384	1.413	1.387	1.375	1.269	1.283	**−0.130**
							(−1.08)
Panel B. 4-Factor Alpha Estimates							
All		0.055	0.074	0.040	−0.215	−0.550	**−0.605**
		(0.98)	(0.96)	(0.42)	(−2.06)	(−3.18)	(−3.29)
Q1 (low)	−0.122	−0.050	−0.074	−0.104	−0.506	−0.922	**−0.972**
	(−1.26)	(−0.69)	(−0.98)	(−0.77)	(−3.15)	(−4.01)	(−3.62)
Q2	−0.032	0.025	0.044	−0.094	−0.450	−0.729	**−0.754**
	(−0.53)	(0.53)	(1.26)	(−1.01)	(−2.58)	(−3.02)	(−2.72)
Q3	0.019	0.026	0.024	−0.076	−0.304	−0.415	**−0.441**
	(0.53)	(0.26)	(0.28)	(−1.05)	(−1.88)	(−2.19)	(−2.57)
Q4	0.007	0.049	0.040	−0.084	−0.109	−0.171	**−0.220**
	(0.09)	(1.42)	(0.68)	(−1.04)	(−1.62)	(−1.85)	(−1.74)
Q5 (high)	0.086	0.107	0.099	0.097	0.023	0.024	**−0.083**
	(2.84)	(2.69)	(1.65)	(1.47)	(0.54)	(0.40)	(−0.81)

negative RTP-return relation is driven by speculative retail trading, then it should be even more negative when a firm is headquartered in (and hence many of its investors come from) a county where gambling activities are more acceptable. In other words, we expect the interaction term to have a negative coefficient estimate if the local gambling environment as captured by CPRATIO influences the RTP-return relation. The estimates reported in column 2 confirm that the RTP $\times$ High CPRATIO coefficient is significantly negative (estimate $= -0.071$, t-statistic $= -2.41$). This evidence indicates that the magnitude of the negative RTP premium is higher for firms that are located in high-CPRATIO regions, again supporting our view that the negative RTP premium reflects the pricing impact of speculative retail trading.

In specifications 3 and 4 of Table 8, we add 4 control variables to account for other potential determinants of average returns: the past 1-month return to account for short-term reversal, the level of institutional ownership, retail BSI

TABLE 8

Retail Trading and Average Returns: Fama-MacBeth Cross-Sectional Regression Estimates

Table 8 reports the estimates from monthly Fama-MacBeth (1973) cross-sectional regressions, where the monthly stock return is the dependent variable. The dependent variable is the raw monthly return in columns 1–3. In column 4, following Asparouhova et al. (2010), we use the past gross-return-weighted monthly return as the dependent variable. The main independent variable is a measure of retail trading (RTP) at the end of the previous month. The monthly RTP is the ratio of the retail trading volume and the total dollar trading volume, where the retail trading volume is the sum of buy- and sell-initiated small-trades dollar volume in the Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases. Other independent variables are the 3 factor exposures (market, small-minus-big (SMB), and high-minus-low (HML) betas), and various firm characteristics (firm size, book-to-market (BM) ratio, past 6-month return, and stock price). The factor exposures are measured "contemporaneously," firm size and 6-month returns are measured in the previous month, and the BM measure is from 6 months ago. In some specifications, we also consider the past 1-month stock return, the level of institutional ownership (IO), retail buy-sell imbalance (BSI), and the illiquidity measure of Amihud (2002), defined as the absolute daily returns per unit of trading volume. All regression specifications use the time period for which the retail trading data are available (1983–2000). The sample period is Jan. 1983–Dec. 2000 in all columns. We follow the Pontiff (1996) methodology to correct the Fama-MacBeth standard errors for potential serial correlation. The *t*-statistics for the coefficient estimates are shown in parentheses below the estimates. To ensure that extreme values are not affecting the results, we winsorize all variables at their 0.5 and 99.5 percentile levels. All independent variables are standardized such that each variable has a mean of 0 and a standard deviation of 1. Only stocks with CRSP share codes 10 and 11 are included in the analysis. The salient numbers are shown in bold.

	Dependent variable is the return of stock *i* in month *t*.			
Variable	1	2	3	4
log(RTP)	**−0.266**	**−0.295**	**−0.388**	**−0.326**
	(−3.75)	(−3.54)	(−4.77)	(−3.59)
log(RTP) × High CPRATIO		**−0.066**	**−0.082**	**−0.079**
		(−2.07)	(−3.23)	(−3.11)
High CPRATIO		−0.024	0.011	−0.008
		(−1.26)	(−1.45)	(−0.32)
Market Beta	0.970	0.972	0.910	0.994
	(4.84)	(4.88)	(3.95)	(5.03)
SMB Beta	0.085	0.086	0.097	0.066
	(0.67)	(0.68)	(1.47)	(0.81)
HML Beta	−0.410	−0.408	−0.403	−0.336
	(−2.74)	(−2.89)	(−2.06)	(−2.55)
log(Firm Size)	−0.367	−0.371	−0.306	−0.367
	(−3.14)	(−3.15)	(−3.17)	(−3.26)
BM	0.247	0.250	0.325	0.232
	(3.49)	(3.57)	(4.05)	(3.49)
Past 6-Month Return	0.011	0.012	0.311	0.231
	(0.52)	(0.81)	(3.65)	(2.87)
log(Stock Price)	−0.145	−0.143	−0.150	−0.367
	(−2.20)	(−2.25)	(−2.67)	(−3.26)
Past 1-Month Return			−0.506	
			(−5.70)	
BSI			0.388	0.329
			(5.24)	(3.43)
IO			−0.018	−0.006
			(−0.74)	(−0.25)
Amihud Illiquidity			−0.003	−0.032
			(−0.14)	(−0.56)
Intercept	1.405	1.404	1.412	1.156
	(3.29)	(3.03)	(3.07)	(3.73)
Avg. no. of stocks	4,593	4,593	4,593	4,584
Avg. adj. R^2	0.048	0.050	0.059	0.041

(Barber et al. (2009)), and the Amihud (2002) illiquidity measure. We include the retail BSI measure in the specification to examine whether our RTP measure reflects the findings of Kaniel et al. (2008) and Barber et al. (2009), who show that stocks heavily bought by individuals 1 week reliably outperform the market the following week.[14] The institutional ownership variable accounts for the possibility that RTP simply reflects the effects of institutional ownership. Specifically, RTP may negatively forecast future returns of stocks because institutions are more informed and better at identifying stocks that would perform well in the future. Therefore, stocks with low institutional ownership (which would have high RTP) would have lower average future returns.

In the extended regression specification reported in column 3 of Table 8, we find that the past 1-month stock return has a strongly negative coefficient estimate, which is consistent with the evidence in Huang, Liu, Ghee, and Zhang (2010). Furthermore, consistent with the evidence in Barber et al. (2009), we find that BSI has a significantly positive coefficient estimate. In contrast, the institutional ownership and illiquidity variables have insignificant coefficient estimates.

More importantly, we find that both RTP and RTP × High CPRATIO coefficient estimates remain significantly negative in the presence of these additional control variables. Those estimates also maintain their significance when we run a weighted least squares regression (see column 4 of Table 8). In this specification, we follow Asparouhova et al. (2010) and define weights based on the gross stock return in the previous month. Overall, the results from our extended specifications indicate that RTP does not merely reflect the short-term return reversal effect (e.g., Jegadeesh (1990), Lehmann (1990)) or the known effects of retail trading imbalance, institutional ownership, and liquidity on stock returns.

C. Negative RTP Premium among Speculative Stocks

In Table 9, we test our 2nd hypothesis that the RTP-return relation is stronger among stocks with speculative characteristics. To do so, we include the interaction of RTP with 2 speculative stock characteristics, namely, IVOL and LOTT in the regressions. The interaction terms would have significantly negative coefficient estimates if the RTP-return relation gets amplified for the subset of speculative stocks.

The regression estimates reported in Table 9 confirm that there is a negative premium associated with both the IVOL and the LOTT variables. Both the IVOL and the LOTT coefficient estimates are significantly negative, where the IVOL coefficient estimate is consistent with the evidence in AHXZ (2009). More importantly, we find that high-RTP stocks underperform by a larger amount if they have higher volatility or have stronger lottery features. Both the High RTP × High IVOL and High RTP × High LOTT coefficient estimates are significantly negative. For example, in column 3, the coefficient for the High RTP dummy variable indicates that stocks ranked in the top ⅓ by RTP is associated with a −0.308% reduction in the mean monthly stock return. This effect is amplified for stocks with high IVOL. The coefficient estimate of the interaction term indicates that the average monthly return on the high-IVOL stocks on average underperforms by

[14]BSI is related to our RTP measure, but there are significant differences. A stock can have a low level of retail trading, but the retail trades could be mostly on the same side, which implies a large (either positive or negative) BSI. There can also be a high level of retail trading in a stock but low BSI. We find that the average cross-sectional correlation between RTP and BSI is only 0.091.

TABLE 9

Retail Trading, Speculative Stock Characteristics, and Average Returns: Fama-MacBeth Cross-Sectional Regression Estimates

Table 9 reports the estimates from monthly Fama-MacBeth (1973) cross-sectional regressions, where the monthly stock return is the dependent variable. The main independent variables include a measure of retail trading (RTP), idiosyncratic volatility (IVOL), and a lottery stock index (LOTT). All these variables are measured at the end of the previous month. The monthly retail trading proportion (RTP) is the ratio of the retail trading volume and the total dollar trading volume, where the retail trading volume is the sum of buy- and sell-initiated small-trades dollar volume in the Institute for the Study of Security Markets (ISSM) and Trade and Quote (TAQ) databases. The IVOL in month t is defined as the standard deviation of the residual from the factor model, where daily returns from month t are used to estimate the model. The LOTT is defined as the sum of the vigintile assignments according to the IVOL, ISKEW, and stock price measures, divided by 60. Here, idiosyncratic skewness (ISKEW) is defined as the scaled 3rd moment of residuals from a factor model that contains market return over the risk-free rate (RMRF) and RMRF^2 as factors. High RTP, High IVOL, and High LOTT are dummy variables that take a value of 1 for stocks that rank in the top 3rd according to the RTP, IVOL, or LOTT measures, respectively. Other independent variables include 3 factor exposures (market, small-minus-big (SMB), and high-minus-low (HML) betas) and 3 firm characteristics (firm size, book-to-market (BM) ratio, and past 6-month return). The factor exposures are measured "contemporaneously," firm size and 6-month returns are measured in the previous month, and the BM measure is from 6 months ago. In specifications 4 and 9, we follow Asparouhova et al. (2010) and use weighted least squares to obtain the regression estimates, where the weight is based on gross return in the previous month. The sample period is Jan. 1983–Dec. 2000 in all columns. We follow the Pontiff (1996) methodology to correct the Fama-MacBeth standard errors for potential serial correlation. The t-statistics for the coefficient estimates are shown in parentheses below the estimates. To ensure that extreme values are not affecting the results, we winsorize all variables at their 0.5 and 99.5 percentile levels. All independent variables except the dummy variables are standardized such that each variable has a mean of 0 and a standard deviation of 1. Only stocks with CRSP share codes 10 and 11 are included in the analysis. The salient numbers are shown in bold.

	Dependent variable is the return of stock i in month t.								
Variable	1	2	3	4	5	6	7	8	9
High RTP		**−0.381**	**−0.308**	**−0.317**		**−0.355**	**−0.317**	**−0.338**	**−0.314**
		(−5.94)	(−4.37)	(−4.33)		(−5.59)	(−5.19)	(−4.67)	(−4.96)
High RTP × High IVOL			**−0.251**	**−0.292**				**−0.185**	**−0.186**
			(−3.76)	(−4.45)				(−3.06)	(−3.56)
High RTP × High LOTT							**−0.214**	**−0.204**	**−0.188**
							(−3.15)	(−2.37)	(−2.04)
IVOL	−0.439	−0.411	−0.306	−0.267				−0.255	−0.249
	(−3.77)	(−3.43)	(−2.76)	(−2.54)				(−2.51)	(−2.40)
LOTT					−0.551	−0.500	−0.377	−0.322	−0.303
					(−5.58)	(−4.27)	(−3.48)	(−3.59)	(−2.60)
Market Beta	1.021	1.023	1.027	1.165	0.928	0.935	0.936	1.023	1.229
	(5.24)	(5.25)	(5.32)	(5.51)	(4.52)	(4.57)	(4.58)	(5.90)	(5.36)
SMB Beta	0.083	0.082	0.085	0.101	0.073	0.072	0.071	0.101	0.104
	(0.81)	(0.79)	(0.81)	(0.82)	(0.67)	(0.65)	(0.65)	(0.85)	(0.80)
HML Beta	−0.450	−0.451	−0.454	−0.501	−0.354	−0.359	−0.360	−0.315	−0.365
	(−2.61)	(−2.54)	(−2.67)	(−2.89)	(−2.85)	(−2.89)	(−2.87)	(−3.35)	(−3.52)
log(Firm Size)	−0.247	−0.331	−0.318	−0.302	−0.362	−0.308	−0.324	−0.340	−0.345
	(−3.36)	(−3.15)	(−3.08)	(−4.00)	(−2.92)	(−2.84)	(−2.98)	(−3.50)	(−4.04)
BM	0.209	0.226	0.230	0.227	0.245	0.257	0.256	0.210	0.201
	(3.63)	(3.41)	(3.99)	(3.52)	(3.92)	(4.09)	(4.15)	(3.38)	(3.24)
Past 6-Month Return	−0.072	−0.096	−0.103	−0.121	−0.024	−0.049	−0.049	0.076	0.074
	(−0.73)	(−0.96)	(−1.04)	(−1.07)	(−0.21)	(−0.43)	(−0.42)	(1.68)	(1.66)
Intercept	1.391	1.207	1.167	1.404	1.261	1.230	1.247	1.339	1.408
	(3.11)	(3.48)	(3.38)	(3.97)	(3.36)	(3.59)	(3.69)	(3.95)	(4.02)
Avg. no. of stocks	4,570	4,570	4,570	4,559	4,570	4,570	4,570	4,570	4,559
Avg. adj. R^2	0.045	0.047	0.048	0.043	0.041	0.043	0.044	0.050	0.046

an additional 0.25% per month when RTP is high. This 0.25% difference is both economically and statistically significant.

For robustness, in column 4 of Table 9, we report the Fama-MacBeth (1973) regression estimates obtained using the Asparouhova et al. (2010) method to account for potential microstructure noise. These results are consistent with the signs of the estimates of the High RTP × High IVOL interaction terms in column 3.

In column 8 of Table 9, we include both IVOL and LOTT variables and the related interaction variables in the same specification to ensure that the LOTT regression results do not simply reflect the IVOL-return relation. We find that both IVOL and LOTT variables still have significantly negative estimates, and their interactions with RTP are also both significant. This evidence indicates that the level of retail trading has a stronger influence on the average returns of stocks with other speculative stock attributes (high ISKEW and low prices) reflected in the LOTT measure. Again, accounting for potential microstructure noise using the Asparouhova et al. (2010) method does not materially change our results (see column 9).

D. Additional Robustness Checks

Table 10 reports several additional robustness tests for the results in Table 9. For brevity we report only the estimates for the main independent variables for each specification.

TABLE 10

Retail Trading, Speculative Stock Characteristics, and Average Returns: Estimates from Robustness Tests

Table 10 summarizes the results from several variations of regression specifications 3 and 7 reported in Table 9. To facilitate comparisons, we summarize the main results from Table 9 as "baseline specifications." In the 1st robustness test, we exclude stocks priced below \$5. In the 2nd test, we estimate the regressions using the 1st half of the 1983–2000 sample period. In the 3rd test, the dependent variable is the characteristics-adjusted monthly stock return instead of the raw monthly return in other regressions. In the 4th test, we add additional controls, including past 1-month stock return, the level of institutional ownership, retail buy-sell imbalance (BSI), and the Amihud (2002) illiquidity measure. In the last robustness test, we include the maximum daily return within a month (MAXRET) proposed in Bali et al. (2011) as an additional independent variable. All other details about the regression specifications are presented in Table 9.

	Dependent variable is the return of stock *i* in month *t*.					
	RTP and IVOL			RTP and LOTT		
	High RTP	High RTP × High IVOL	IVOL	High RTP	High RTP × High LOTT	LOTT
Test	1	2	3	4	5	6
1. Baseline Estimates	−0.308	−0.251	−0.306	−0.317	−0.214	−0.377
	(−4.37)	(−3.76)	(−2.76)	(−5.19)	(−3.15)	(−3.48)
2. Stock Price ≥ \$5	−0.282	−0.181	−0.302	−0.205	−0.105	−0.342
	(−3.76)	(−2.79)	(−2.44)	(−3.75)	(−2.18)	(−2.74)
3. 1983–1991 Period	−0.311	−0.240	−0.236	−0.315	−0.172	−0.401
	(−3.29)	(−4.38)	(−2.26)	(−4.99)	(−2.50)	(−3.01)
4. Use Char-Adj Returns	−0.221	−0.165	−0.102	−0.296	−0.205	−0.218
	(−4.33)	(−3.17)	(−1.22)	(−5.95)	(−2.57)	(−2.38)
5. Additional Controls	−0.301	−0.252	−0.069	−0.336	−0.209	−0.371
	(−4.68)	(−3.63)	(−1.06)	(−5.35)	(−2.98)	(−3.39)
6. Control for MAXRET	−0.212	−0.221	0.378	−0.311	−0.206	−0.396
	(−3.35)	(−6.33)	(4.18)	(−4.66)	(−3.03)	(−4.47)

In the 1st test, we exclude stocks priced below \$5 and find that the RTP, IVOL, LOTT, and the 2 interaction terms have qualitatively similar estimates. When we estimate the IVOL and LOTT regressions for the 1983–1991 sample period, we find the results are weaker but remain similar to the full-sample estimates. In the 3rd robustness test, we ensure that our key results are not influenced by the specific choice of the risk adjustment model. We reestimate the IVOL and LOTT regressions using characteristic-adjusted returns, where we also control for risk by including the factor exposures in the regression specification. Again, we find that all key independent variables maintain their statistical significance levels and their signs.

In the last 2 robustness tests, we include additional control variables in the regression specifications. When we include past 1-month stock return, institutional ownership, retail BSI, and Amihud (2002) illiquidity measure in the specification, the High RTP and High RTP × High IVOL remain significantly negative in both IVOL and LOTT regression specifications. However, consistent with the evidence in Huang et al. (2010), we find that IVOL loses its statistical significance.[15] In contrast, the LOTT variables remain significantly negative even in the presence of a control for the short-term reversal effect.

When we include the maximum daily return within a month (MAXRET) measure proposed in Bali, Cakici, and Whitelaw (2011) as an additional independent variable, consistent with their evidence, the IVOL coefficient estimate becomes positive. However, again, the LOTT variable remains significantly negative even in the presence of MAXRET. Furthermore, the High RTP × High IVOL and High RTP × High LOTT interaction terms continue to have significantly negative coefficient estimates. This evidence indicates that although the volatility-return relation switches sign in the presence of MAXRET, stocks with high IVOL continue to earn lower incremental returns when the level of retail trading is high. Furthermore, this evidence indicates that the MAXRET measure does not alter the negative relation between the LOTT and stock returns.

V. Summary and Conclusion

In this paper, we introduce the retail trading proportion (RTP) variable for individual stocks constructed from their trading records and show that it effectively captures the speculative trading activities of retail investors. Stocks with lottery features (high volatility, high skewness, and low prices) are heavily traded by retail investors and, thus, have high RTP, while institutions underweight those stocks. Furthermore, the characteristics of the retail clienteles of high-RTP stocks are remarkably similar to the characteristics of investors who are attracted to lottery-type stocks (Kumar (2009)). RTP is also high for firms that are headquartered in regions where people exhibit a greater propensity to gamble. And consistent with the realization utility model of Barberis and Xiong (2012), we show that investors' propensity to realize gains is stronger among high-volatility stocks and stocks with high levels of retail trading.

Examining the asset pricing implications of speculative retail trading, we find that high-RTP stocks tend to be overpriced. We show that stocks with high levels of retail trading significantly underperform low-retail-trading stocks, where the high-low RTP return differential (i.e., the RTP premium) is about −7% annually. The negative RTP premium is stronger among stocks that have lottery features or are located in regions in which people exhibit a stronger propensity to gamble.

[15]Huang et al. (2010) show that the volatility-return relation is insignificant when past 1-month return is used as a control variable.

Our results are consistent with noise trader models in general, and in particular, several recent behavioral models that show that investors' willingness to pay a premium for stocks with lottery features and high realization utility potential can cause mispricing for these stocks (e.g., Barberis and Huang (2008), Barberis and Xiong (2012)).

Taken together, our empirical findings contribute to the recent retail investor literature, which documents that retail trading can affect stock prices and forecast future stock returns (e.g., Kumar and Lee (2006), Barber et al. (2009), Dorn et al. (2008), Hvidkjaer (2008), and Kaniel et al. (2008)). The evidence also highlights the usefulness of a habitat-based approach for studying asset prices. Future research may find it fruitful to examine whether our retail clientele proxy can help explain other related asset pricing anomalies such as the negative relation between distress risk and stock returns.

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