The Impact of Individual Investor Trading on Stock Returns

Zhijuan Chen, William T. Lin, Changfeng Ma, and Zhenlong Zheng

ABSTRACT: In this paper, we study the impact of the trading of individual investors on short-horizon stock returns from 2005 to 2006 using a unique data set provided by the Taiwan Stock Exchange. We examine the predictability of stock returns based on net individual trading by using the portfolio-sorting approach and the Fama–MacBeth regression method. Contrary to previously offered conclusions, we find that the imbalance in individual trading negatively predicts future stock returns on a stock-by-stock basis, which indicates that individual investors can be viewed as noise traders to some extent. At the same time, using the principal component analysis, we find that the noise trading of individuals is not systematic.

KEY WORDS: individual investors, noise traders, stock returns, systematic.

In this paper, we study whether the trading of individual investors in Taiwan affects stock returns in a short time horizon. This issue is important for an understanding of the relationship between the pattern of stock returns and individual investor trading in emerging markets. It has previously been addressed with regard to mature markets only. For example, Kaniel et al. (2008) use a unique New York Stock Exchange (NYSE) data set to examine the short-horizon dynamic relationship between individuals' trading and stock returns and document a positive correlation between net individual trading (NIT) and future returns. Similarly, Jackson (2003) also finds that the net flows of small investors positively predict future short-horizon returns in Australia.

Each of these papers offers an excellent analysis of mature stock markets with a majority of institutional investors. However, the increasingly growing emerging markets with a majority of individual investors have yet to be carefully explored with regard to the question of individual investors' influence on stock returns. Accordingly, we aim to fill this gap by investigating this issue in the stock market in Taiwan, which is an important

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emerging market. We use the portfolio-sorting approach and Fama–MacBeth regression to test the predictability of returns using the trading imbalance of individual investors. Although Andrade et al. (2008) and Barber et al. (2008) also investigate Taiwan's stock market and report that Taiwanese individuals tend to lose money over short horizons, they do not focus on the short-horizon dynamic relationship between individual investors' trading and stock returns. Lin et al. (2012) also investigate Taiwanese individuals' trading behaviors, but they instead focus on the impact of search costs on individual trading.

An important related question is whether individual trading is systematic in the sense that it affects all stock returns at the same time, an extremely important issue in asset pricing. However, the literature offers mixed answers to this question. Barber et al. (2009a, 2009b), Jackson (2003) and Kumar and Lee (2006) show that individual trading is systematically related, but Kaniel et al. (2008) do not "find strong evidence of a common component in the imbalances of individual investors across stocks." Like Kaniel et al. (2008), we conduct a principle component analysis and find that the noise-trading behaviors of individual investors have no significant systematic features.

Our main contribution to the literature has three dimensions. First, our study of the relationship between Taiwanese individual trading and future returns extends the existing literature on mature markets to emerging markets. Second, this paper provides evidence that NIT negatively predicts future returns in a market mainly composed of individual investors, which is in opposition to the conclusions in the existing literature on mature markets. Finally, our evidence shows that individual trading is not systematic, which is contrary to the systematic effects of individual investor trading that others have found.

Data Description and NIT

Our tick-by-tick data set is a complete record of stock transactions from January 1, 2005, to December 31, 2006, provided by the Taiwan Stock Exchange (TSE), including the transaction date, stock code, trade direction (buy or sell), transaction time, transaction price, and transaction volume. One advantage of our data is that five types of investors—namely, individuals, mutual funds, proprietary dealers, firms, and foreigners—are clearly marked, which enables us to identify individual investors precisely rather than inferring this by some algorithm with insufficient accuracy.

We aggregate tick data to get daily data for trading volume. We obtain the market capitalization of each stock on each day by multiplying the number of outstanding stock shares by the closing price that day. According to the market capitalization of each stock, stocks are sorted into ten deciles from which we form three size groups: deciles 1, 2, and 3 are classified as small stocks, deciles 4, 5, 6, and 7 are classified as mid-cap stocks, and deciles 8, 9, and 10 are classified as large stocks. The daily returns of individual stock and market portfolio returns (transaction price returns) are from the *Taiwan Economic Journal.* Then we obtain excess returns of portfolios by the value-weighted average of excess individual stock returns relative to market returns.

Following Kaniel et al. (2008) we adopt NIT as an indicator of individual trading imbalance. NIT for stock i on day t can be defined as follows:

$$NIT_{i,t} = \frac{IBV_{i,t} - ISV_{i,t}}{AV_{i,t-1}}, \tag{1}$$

where $IBV_{i,t}$ is the dollar volume (in New Taiwan dollars, NT$) of individuals buying stock i on day t, $ISV_{i,t}$ is the dollar volume (NT$) of individuals selling stock i on day

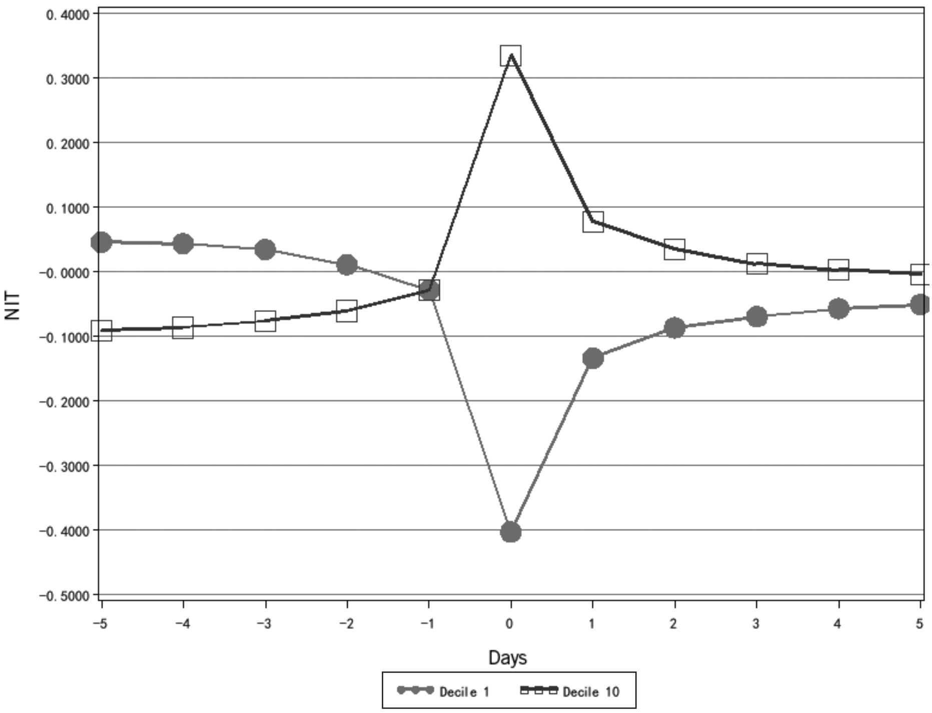

Figure 1. NIT measures of portfolios around formation day

t, and $AV_{i,t-1}$ is the average daily dollar volume of stock i for the previous month ending on day $t - 1$. It should be noted that when we compute $AV_{i,t-1}$, we use the rolling month rather than the calendar month, which helps to maintain the continuity of the net trading indicator with the result that there is no obvious jump.

To examine the relationship between NIT and future returns, following Kaniel et al. (2008), we dynamically rank each stock into decile 1 (intense selling), ..., decile 10 (intense buying) by comparing its NIT with that of the previous nine days.

Figure 1 presents the NIT measures of decile 1 and decile 10 of stocks during, before, and after the portfolio formation day, respectively. Decile 1 contains the stocks with the most intense selling (negative NIT), while decile 10 contains the stocks with the most intense buying (positive NIT).

Figure 1 shows the NITs of the stocks of decile 1 and decile 10 around the formation day. It is obvious from the figure that the trading activity of individuals is more intense during the formation day than before or after the formation day, which indicates that individual investors do not consistently trade the same stocks. Thus, the portfolio formed by the above procedure contains different stocks on different days.

Using the same procedure as above, on each day we categorize stocks into five quintiles, namely Q1 (intense selling), Q2, Q3, Q4, and Q5 (intense buying), to provide summary statistics. Table 1 shows the time-series description statistics for the average NIT of stocks in Q1 to Q5. It can be seen from Table 1 that the average magnitude of NIT ranges from –30.90 percent (intense selling) to 25.43 percent (intense buying), which spans a very large range.

Table 1. Summary statistics of NIT in five portfolios

Portfolio	Mean	Standard deviation	25%	Median	75%
1	–0.3090	0.6569	–0.3686	–0.1455	–0.0360
2	–0.0954	0.2070	–0.1323	–0.0295	–0.0003
3	–0.0128	0.5234	–0.0396	0.0000	0.0190
4	0.0567	0.1918	0.0000	0.0168	0.0903
5	0.2543	1.3180	0.0239	0.1134	0.2936

Predictability of Returns Using NIT

We investigate the relationship between the trading of individual investors and stock returns through an examination of the short-horizon prediction of stock returns based on the trading behaviors of individual investors in Taiwan. Jegadeesh (1990) and Lehmann (1990) document the predictability of future returns by past returns. Conrad et al. (1994), Datar (1998), Gervais et al. (2001) and Llorente et al. (2002) show that trading volume is relevant with regard to the predictability of stock returns. For example, Gervais et al. (2001) point out that volume increases the predictability of returns. As a result, past returns and volume should be controlled for when we analyze the predictability of returns using the trading behaviors of individual investors.

Portfolio-Sorting Approach

We first form twenty-five portfolios by independently placing stocks into five quintiles based on their historical daily returns and five quintiles based on their NIT decile rankings for the day. For each portfolio, the value-weighted market-adjusted return on the following day is computed. Panel A of Table 2, reporting the time-series average of the daily market-adjusted returns for the twenty-five portfolios, indicates that the daily stock returns can be predicted by NIT even after controlling for past returns.

The bottom two rows of this panel present the payoffs for buying a portfolio that is composed of stocks that experienced more intense individual buying on the previous day (NIT quintile 5) and selling those stocks that experienced intense individual selling (NIT quintile 1) in each return quintile. Panel A of Table 2 shows that all of these portfolios suffer statistically significant negative payoffs, ranging from –0.2253 percent to –0.474 percent per day. Panel B of Table 2, showing the results of the analysis of the same portfolio sorting procedure based on NIT decile rankings and turnover decile rankings,[1] suggests that NIT is still able to significantly and negatively predict stock returns even after controlling for turnover.

Fama–MacBeth Regression

In order to ensure that the predictability of returns using NIT is not caused by past returns and trading volume simultaneously, we regress returns of day $t + 1$ on returns of day $t - 1$,[2] turnover decile and NIT decile of day t using Fama and MacBeth's (1973) regression method. The regression equation is as follows:

$$R_{i,t+1} = \alpha + \beta_1 R_{i,t-1} + \beta_2 NITDecile_{i,t} + \beta_3 TurnoverDecile_{i,t} + \varepsilon_{t+1}. \qquad (2)$$

Table 2. Predictability of returns: portfolio-sorting results

Panel A: Daily predictability of returns using past returns and NIT

	Return(t – 1)				
NIT(t)	Q1	Q2	Q3	Q4	Q5
Q1	0.2081	0.1795	0.1207	0.0600	0.1699
Q2	0.2596	0.0921	0.0707	0.0339	–0.0321
Q3	0.0896	–0.0111	0.0000	–0.0449	–0.0144
Q4	0.0663	0.0000	–0.0205	–0.0816	–0.1715
Q5	–0.1060	–0.0733	–0.1874	–0.1619	–0.3018
Q5–Q1	–0.3150***	–0.2530***	–0.3096***	–0.2253***	–0.4740***
t-statistic	(–5.0434)	(–5.1090)	(–6.9463)	(–4.6441)	(–8.2022)

Panel B: Daily predictability of returns using past turnover and NIT

	Turnover(t)				
NIT(t)	Q1	Q2	Q3	Q4	Q5
Q1	0.0918	0.0733	0.1100	0.0916	0.1381
Q2	0.0963	0.1051	0.0540	0.0322	0.0436
Q3	–0.0031	0.0142	0.0065	–0.0767	–0.0323
Q4	–0.0276	–0.0868	–0.0461	–0.0653	0.0063
Q5	–0.1207	–0.1058	–0.1849	–0.1859	–0.2086
Q5–Q1	–0.2123***	–0.1816***	–0.2990***	–0.2764***	–0.3468***
t-statistic	(–3.9555)	(–3.2552)	(–6.1414)	(–5.1100)	(–6.4787)

Notes: In Panel A, on each day t, we divide stocks into five quintiles according to NIT and return of day t – 1, and then we get twenty-five portfolios as the intersection of five NIT quintiles and return quintiles. We compute the time-series of market-adjusted return for each portfolio and present their means and Newey–West corrected t-statistics. The last two rows give the payoffs to the strategy of buying NIT quintile 5 and selling NIT quintile 1 across return quintiles. In Panel B, the same procedure is applied only with return of day t – 1 is replaced by turnover. *** Significance at the 1 percent level; ** significance at the 5 percent level; * significance at the 10 percent level.

As the test result can be influenced by stock size, we also give the test statistics of the three sizes of stocks: small, mid-cap, and large. Table 3 shows the results of the regression analysis.

Table 3 shows that almost all of the coefficients of NIT are negative and highly statistically significant in both the univariate and the multivariate regressions, which is consistent with the findings of the portfolio-sorting approach. Our results show that the coefficient of NIT is still significantly negative even when past returns and trading volume are considered. Thus, we can conclude that individual investors lack information when trading stocks, indicating that their trading is not driven by informational factors, but rather by some psychological biases. Therefore, we can identify individual investors as noise traders to some extent.

Systematic Testing

While we have documented the negative dynamic relationship between NIT and returns on a stock-by-stock basis, we now examine whether this relation exists in a systematic sense.

Table 3. Predictability of returns: the Fama–MacBeth Regression

Size groups	Intercept (*t*-statistic)	*Return* (*t*-statistic)	*NITDecile* (*t*-statistic)	*TurnoverDecile* (*t*-statistic)
All stocks	0.0590	–0.0013		
	(1.1052)	(–0.2280)		
	0.2356***		–0.0294***	
	(4.3930)		(–15.9156)	
	0.0778			–0.0013
	(1.5079)			(–0.4219)
	0.2229***	–0.0066	–0.0296***	–0.0004
	(4.3841)	(–1.1558)	(–16.7046)	(–0.1580)
Large stocks	0.0669	–0.0152**		
	(1.3800)	(–2.2090)		
	0.3291***		–0.0454***	
	(6.6600)		(–14.2318)	
	0.1149**			–0.0076**
	(2.3669)			(–2.0833)
	0.3737***	–0.0285***	–0.0489***	–0.0067**
	(7.8491)	(–4.2181)	(–16.2541)	(–1.9653)
Mid-cap stocks	0.0650	–0.0068		
	(1.1550)	(–0.9883)		
	0.2558***		–0.0319***	
	(4.3112)		(–13.8251)	
	0.1154**			–0.0064**
	(2.0557)			(–2.0085)
	0.2617***	–0.0102	–0.0313***	–0.0050*
	(4.5327)	(–1.5273)	(–14.2552)	(–1.7835)
Small stocks	0.0349	0.0047		
	(0.5742)	(0.6477)		
	0.0617		–0.0038	
	(1.0417)		(–1.0504)	
	0.0176			0.0044
	(0.2883)			(0.9891)
	0.0256	0.0021	–0.0041	0.0055
	(0.4044)	(0.2761)	(–1.2067)	(1.2375)

Notes: This table shows the regression result of the daily predictability of returns. The independent variables are an intercept, *Return*, *NITDecile*, and *TurnoverDecile*. We implement a Fama–MacBeth method reporting Newey–West corrected *t*-statistics. *** Significance at the 1 percent level; ** significance at the 5 percent level; * significance at the 10 percent level.

Following Kaniel et al. (2008), we conduct a principal component analysis of daily NIT to achieve this goal. Among the stocks with a complete set of daily returns, we construct 1,000 random subsamples of sixty stocks.[3] We then look at the mean and standard deviation of the percentage of variance of NIT that can be explained by the first ten principle components across these 1,000 random subsamples. In order to develop a benchmark for evaluating the percentage of variance explained by the principal components in the real data, we use numerical simulations to generate principal components for independent random matrixes.[4] Then, the differences between the real means and simulated means of the percentage of variance of NIT explained by the first ten principle components acts as the measure of the structure in the real data.

Table 4. Principal component analysis of NIT at the daily frequency: percentage of variance explained by principal components (random samples of stocks)

NIT	PC1	PC2	PC1–5	PC1–10
Real mean	0.0438	0.0374	0.1774	0.3110
Real standard	0.0041	0.0020	0.0096	0.0129
Simulated mean	0.0292	0.0281	0.1369	0.2581
Difference	0.0146	0.0093	0.0405	0.0529

Notes: We first get the variance explained by the first five and ten principal components in the real and simulated data. Finally, we present the difference of variance explained by the first five and ten principal components between the real and simulated data.

Table 4 shows that the difference between the real and simulated means of the percentage of variance of NIT explained by the first five and ten principle components is 4.05 percent and 5.29 percent, respectively. Moreover, the first (and largest) principal component of NIT explains only 1.46 percent of the variance, indicating that we do not find evidence of common components in the imbalances of individual investors across stocks.

Kumar and Lee (2006) and Lee et al. (1991) argue that stocks with different sizes suffer different intensities of noise trading. Therefore, we categorize stocks into TEN deciles according to each stock's market value and look at the difference between the real and simulated means of principal components to measure the common components in NIT across stocks in that portfolio.[5] Contrary to expectations based on the above papers but consistent with Kaniel et al. (2008), the percentage of NIT variance explained by the first five principal components is higher for large stocks (11.8 percent for decile 10) than it is for small stocks (0.28 percent for decile 1). However, the magnitude is still very small even for large stocks, indicating that there seems to be no strong evidence of the existence of significant common components in NIT across stocks—even in large stocks. In broad terms, we do not find strong evidence that NIT is correlated across stocks, and individual noise trading seems to cancel itself out.

Conclusions

Given the interesting nature of noise-trading theory, this paper has investigated whether the trading of individual investors affects stock returns over short horizons. This paper has focused on the individual trading of an emerging stock market, namely the stock market in Taiwan, rather than that of a mature stock market. The distinguishing feature of Taiwan's stock market is that it is largely occupied by individual investors, which increases the importance of research regarding whether Taiwanese individual trading behaviors affect stock prices.

Following Kaniel et al. (2008), we use NIT to measure the trading behaviors of individuals. Using this indicator and a high-quality data set from the TSE, we first find that NIT can significantly predict negative returns over short horizons. We adopt both the portfolio-sorting approach and the Fama–MacBeth regression method to show that the negative relation between excess returns and NIT is still significant even after controlling for trading volume and past returns. This empirical analysis provides strong evidence that individual investors demonstrate some features of noise trading.

To study whether the effect of individual trading behaviors is systematic, we use a principal component analysis of the individual trading imbalance. Our empirical analysis indicates that individual trading is not systematic, so that individuals' trading does not systematically affect asset prices, which means that policy makers do not need to consider the price impact of individual trading on the stock market when they devise trading rules.

Notes

1. Following Kaniel et al. (2008), trading volume is represented by turnover, the decile ranking of which is obtained by comparing a certain stock's turnover (number of shares traded divided by the number of shares outstanding) each day with that of the same stock in the previous nine days, similar to the method of determining NIT decile rankings.
2. Note that we use returns on day $t - 1$ rather than t to be consistent with the portfolio-sorting approach.
3. Sixty is approximately one-tenth of the number of stocks (570) having a complete set of daily returns and is therefore roughly comparable to the number of stocks in a size decile.
4. For the details of the procedure, see Kaniel et al. (2008).
5. We do not show the results, but it is available from the authors on request.

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