Who Is the More Overconfident Trader? Individual versus Institutional Investors

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Abstract

Guided by the Gervais and Odean (2001) overconfident trading hypothesis, we comprehensively investigate the trading behavior of individual versus institutional investors in Taiwan in an attempt to identify who is the more overconfident trader. Conditional on the various states of the market, on market volatility, and on the risk level of the securities they trade, we find that both individual and institutional investors trade more aggressively following market gains in bull markets, in up-market states, in up-momentum market states, and in low-volatility market states and that only individual investors trade more in riskier securities following market gains. More importantly, we find that individual investors trade more aggressively following market gains in the three conditional states of the market and in high-volatility market states than institutional investors. Also, individual investors trade more in relatively riskier securities following gains than institutional investors. These findings provide evidence that individual investors are more overconfident traders than institutional investors.

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1. Introduction

It has long been argued that trading volume in financial markets is too large to be justified on rational grounds (see, for example, Ross (1989a)). Excess trading volume is one puzzle representing a great challenge to the field of finance. De Bondt and Thaler (1995) argue that overconfidence plays a key role in solving this puzzle. Along this line of thinking, there are a growing number of theoretical models rooted in investor overconfidence to account for the observed excess trading volume in financial markets. For example, the self-learning model proposed by Gervais and Odean (2001) predicts that biased investors overestimate the degree to which they contribute to returns from general market increases, the process of wealth accumulation makes them overconfident, and therefore they trade more aggressively following market gains.[1] Along this line of argument, Odean (1998) argues that excess trading volume is the most robust effect of overconfidence.

Several empirical studies present evidence that overconfidence plays a pivotal role in explaining individual investors' propensity to trade too much and too speculatively. For example, Odean (1999) and Barber and Odean (2000) find that U.S. individual investors with discount brokerage accounts appear overconfident about their perceived information and ability to trade in that they trade too much and too speculatively, yet their active trading

[1] A similar argument that overconfidence leads to greater trading is also made in De Long, Shleifer, Summers, and Waldmann (1991), Kyle and Wang (1997), Benos (1998), Odean (1998), Wang (1998, 2001), Daniel, Hirshleifer, and Subrahmanyam (2001), Hirshleifer and Luo (2001), Caballé and Sákovics (2003), and Scheinkman and Xiong (2003).

detracts from their performance. Barber and Odean (2002) find that those who switch to online trading perform well prior to going online, which engenders greater overconfidence. They find that after going online, these investors trade more actively, more speculatively, and less profitably than before.[2]

Odean (1998, 1999) and Gervais and Odean (2001) argue that people who are more overconfident in their investment abilities may be more likely to seek jobs as traders or to actively trade on their own accounts. If so, we might expect to observe that financial markets are populated by overconfident investors. Many researchers also argue that overconfident investors can survive and dominate markets in the long run (e.g., Kyle and Wang (1997), Benos (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Gervais and Odean (2001), Hirshleifer and Luo (2001), and Wang (2001)). These arguments imply that it is possible to detect investors' aggregate overconfident trading behavior from the market level if overconfidence is a systematic cognitive bias from which most investors suffer.

Focusing on the aggregate overconfident trading behavior of U.S. investors, Statman, Thorley, and Vorkink (2006) and Chuang and Lee (2006) find that high market-wide returns are followed by high market-wide trading volume, and they interpret their finding as consistent with the theoretical prediction of the Gervais and Odean (2001) model that market gains make investors overconfident and consequently they trade more actively in

[2] The notion that overconfidence leads individual investors to trade too much and too speculatively is also empirically supported by several experimental studies (e.g., Von Holstein (1972), Biais, Hilton, Mazurier, and Pouget (2005), Glaser and Weber (2007), and Deaves, Lüders, and Luo (2009)).

subsequent periods. Consistent with the overconfidence hypothesis, Chuang and Lee (2006) also find that U.S. investors' overconfident trading is higher in bull markets than in bear markets, when their forecasts are correct more often than wrong, and that they trade more in riskier securities after market gains than in less risky securities.

Some psychologists present evidence that Asians exhibit overconfidence in general knowledge (e.g., Yates, Lee, and Shinotsuka (1996) and Yates, Lee, and Bush (1997)). This makes Asian markets, such as Taiwan, very good platforms upon which to test the overconfidence hypothesis. Using a complete trading dataset of all Taiwanese investors, Barber, Lee, Liu, and Odean (2009) find that individual investors trade to their significant detriment, which can be traced to their aggressive trades. They argue that overconfidence and entertainment are two reasons that explain why individual investors trade so speculatively. On the other hand, they find that institutional investors earn positive abnormal returns from both their passive and aggressive trades. Since individual investors may also trade for fun, it is still not altogether clear from Barber et al. (2009) whether individual investors are more overconfident traders than institutional investors.

In this paper, we also focus on the Taiwanese stock market to test Gervais and Odean's (2001) overconfident trading hypothesis. In particular, we examine the trading behavior of individual versus institutional investors in Taiwan. For this purpose, we form size- and volume-institutional ownership portfolios that are different in terms of institutional ownership but similar in terms of firm size and trading volume, respectively, for stocks listed on the Taiwan Stock Exchange (TSE). First, in a preliminary analysis, we find a significant positive causal relation between current portfolio volume and lagged market returns for all portfolios. Then, we examine this positive causal relation across the low and high institutional ownership portfolios within each size and volume quartile by using a Seemingly Unrelated Regressions (SUR) model. Our results show that this positive causal relation is significantly stronger for the portfolios with low institutional ownership than for the portfolios with high institutional ownership. This implies that market gains make individual investors trade more aggressively in subsequent periods than institutional investors.

To gain more insight into the overconfident trading behavior of Taiwanese investors, we follow and extend Chuang and Lee (2006) to analyze how investors behave conditional on the various states of the market, on market volatility, and on the risk level of the securities they trade. All these conditional events are suggested by behavioral finance theory. Using this conditional framework, first, we find that both individual and institutional investors trade more actively subsequent to market gains in bull markets, in up-market states, and in up-momentum market states than in bear markets, in down-market states, and in down-momentum market states, respectively.[3] Second, we find that both individual and

[3] We use the economic monitoring indicators released by the Council for Economic Planning and Development (CEPD) in Taiwan to define the bull and bear markets. We follow Cooper, Gutierrez, and

institutional investors trade more actively following market gains in low-volatility market states than in high-volatility market states and that individual investors trade more actively following market gains in high-volatility market states than institutional investors. And, finally, we find that only individual investors tend to underestimate risk and trade more in riskier securities subsequent to market gains. More importantly, we find that individual investors trade more actively following market gains in these conditional events than institutional investors, together with the finding that the trading performance of individual investors is worse than that of institutional investors, indicating that individual investors are more overconfident traders than institutional investors.

Finally, we relate our findings to the two strands in the literature that analyze the overconfidence of individual versus institutional investors. On one side, Griffin and Tversky (1992) argue that when predictability is very low, professionals may be even more overconfident than novices and amateurs. On the other side, Gervais and Odean (2001) argue that less experienced traders will be more overconfident than more experienced traders. In general, individual investors as a group are regarded as less experienced, amateurish investors, while institutional investors as a group are regarded as more experienced, professional investors. Overall, consistent with Gervais and Odean's (2001)

Hameed (2004) to define the up- and down-market states and follow Jegadeesh and Titman's (1993, 2002) weighted relative strength strategy to define the up- and down-momentum market states. These different states of the market are devised to capture the difference in investors' overconfident trading behavior. For detail, see our discussion in Section 3.3.

argument, we find that individual investors are more overconfident traders than institutional investors.

This paper contributes to the overconfidence literature along three lines. First, our comprehensive empirical examination provides more evidence on the issue of whether individual investors are more overconfident traders than institutional investors. Although, as noted by Barber et al. (2009), individual investors may trade for fun, it is hard to argue that they do so particularly in bull markets, in up-market states, in up-momentum market states, and in low-volatility market states. Second, unlike prior studies that find either that investors trade more actively after market gains or that institutional investors enjoy better trading performance than individual investors, we find that individual investors trade more actively after market gains and their trading performance gets worse than institutional investors. Our results verify the notion that overconfidence implies non-optimal decisions by showing that individual investors' active trading after market gains reduces their performance. Third, we find that investors' overconfident trading varies in up- and down-market states, in up- and down-momentum market states, and in low-, medium-, and high-volatility market states. These issues are not explored in prior studies and our findings advance our understanding of investors' overconfident trading behavior.

The paper is organized as follows. Section 2 introduces the data, describes the method to filter trading volume series to achieve stationarity, and reports some descriptive statistics.

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Section 3 introduces our various empirical frameworks that are devised to detect the overconfident trading behavior of Taiwanese individual and institutional investors and to compare the relative degree of their overconfident trading behavior, and presents and discusses the empirical results. Finally, we conclude the paper in Section 4.

2. Background, data and detrending trading volume series

2.1. Taiwan market rues

Before proceeding, it is useful to characterize the Taiwan Stock Exchange (TSE). The TSE is an order-driven call market where only limit orders are accepted. Unlike U.S. stock markets, there are no formal designated market makers or specialists. All securities listed on the TSE are traded through the Fully Automated Securities Trading (FAST) system. Orders are executed according to the rule of strict price and time priority. Therefore, an order entered into the FAST system at an earlier time should be fully executed before an order at the same price entered at a later time is executed.

Institutional investors in Taiwan are classified into five categories: corporate institutions, financial institutions, mutual funds, securities dealers, and foreign investors.[4] Although the majority of participants in the TSE are individual investors, institutional investors have become gradually more active over time and, therefore, play an increasingly

[4] In Taiwan, corporate institutions include Taiwanese corporations and government-owned firms. The mean averages of share ownership by Taiwanese corporations and government-owned firms from 1996 to 2007 were 21.74% and 5.43%, respectively. In addition to this, since government-owned firms tend to follow government policy to stabilize the market and might not pursue profit-maximizing objective to actively trade in the stock market, it is expected that Taiwanese corporations would contribute the most to corporate trading.

important role in the Taiwanese stock market. For example, at the start of our sample, domestic and foreign institutional investors accounted for 10% of total trading volume (NT$ 822 billion); but by the end of our sample, in 2007, institutional investors accounted for 31% of total trading volume (NT$ 20,370 billion).[5] Table 1 reports the individual and institutional annual trading volume from 1996 to 2007.

During our sample period, investors faced several trading regulations in the TSE. First, there is a daily price limit of 7% in each direction based on the closing price of the preceding trading day for all traded stocks. Second, securities dealers were prevented from submitting orders above or below 3.5% of the opening price that is determined by selecting the price to maximize matched trading volume. Third, individual investors and corporate institutions (both Taiwanese corporations and government-owned firms) were allowed to sell short stocks only at a price above the last transaction price or at a price equal to the last transaction price if the most recent price movement was upward; however, mutual funds, securities dealers, and foreigner investors were precluded from doing so.[6] Barber, Lee, Liu, and Odean (2007) show that 8.37% of individual investors and 4.52% of corporate

[5] The Taiwanese stock market has historically imposed several limitations on foreign investment. In 1991, Qualified Foreign Institutional Investors (QFIIs) were permitted to directly invest in the Taiwanese stock market, with a ceiling of investment quotas of US$50 million and the minimum investment amount of US$ 5 million for a single QFII and a ceiling of total investment quotas of US$2.5 billion for all QFIIs. The maximum ratio for each foreign investor's holdings in individual listed firms were originally set at 5% in 1991, and were gradually increased to 10% in 1996, and 50% in 2000. The ceiling for total investment quotas for all QFIIs was removed in 1995. Finally, the regulation of the maximum and minimum investment amounts for a single QFII was canceled in 1996 and 2003, respectively.

[6] On May 16, 2005, the TSE has removed the up-tick rule on the component stocks of the Taiwan 50 index, and, hence, these stocks were allowed to be sold short below the previous closing price.

institutions are short sellers during their sample period from 1995 to 1999. Thus, on average, short sales represent only a small fraction of individual and institutional investors' trading in the TSE.

2.2. Data

Our dataset comprises all common stocks listed on the TSE. To be included in our sample, a stock must have available information on weekly stock returns, weekly trading turnover, weekly market capitalization, and the monthly fraction of shares held by institutional investors.[7] These variables are extracted from the *Taiwan Economic Journal* (TEJ) database. Based on Lo and Wang (2000), we use trading turnover, defined as the ratio of the number of shares traded in a given day to the total number of shares outstanding at the end of the day, as a measure of trading volume (see also Statman et al. (2006) and Chuang and Lee (2006)). Fractional institutional ownership is defined as the ratio of the number of shares held by institutional investors to the number of shares outstanding. The weekly data of stock returns, trading turnover, and market capitalization cover the period from January 6, 1996, to May 25, 2007, and the monthly data of fractional institutional ownership cover the period from December 1995 to April 2007.

[7] Before December 1997, Saturday trading occurred from 9:00am-11:00am. From January to March, 1998, trading occurred only on the second and the fourth Saturday in each month. From April 1998 to December 2000, stocks were traded from 9:00am to noon. From 2001 on, there has been no trading on Saturday. When there was Saturday trading (no Saturday trading), the weekly return and turnover of each stock are computed using Saturday's (Friday's) closing price to the following Saturday's (Friday's) closing price and computed as a summation from Monday's turnover to Saturday's (Friday's) turnover, respectively. The definition of the weekly turnover by the TEJ is consistent with that of the time-aggregation turnover by Lo and Wang (2000).

Our research strategy is to form low and high institutional ownership portfolios in order to contrast the trading behavior of individual versus institutional investors. However, previous studies have documented that stocks held by more institutional investors tend to experience higher returns and have larger firm size and higher trading volume (e.g., Badrinath, Kale, and Noe (1995), Sias and Starks (1997), Sias (2004), Rubin (2007), and Bailey, Cai, Cheung, and Wang (2009)). These findings naturally raise the question of whether the differences in trading behavior between the low and high institutional ownership portfolios can really point to the differences in trading behavior between individual and institutional investors. Instead, the differences could be due to the fact that stocks with different characteristics are traded differently by *all* investors. To avoid this problem, we divide our sample of stocks in the following manner. For the period from January 1996 to May 2007, four size quartiles are formed at the beginning of each month by ranking all sample stocks by their market capitalizations. Then, each size quartile is further classified into two groups based on the monthly fraction of shares held by institutional investors. Thus, each sample stock is assigned to one of 8 size-institutional ownership portfolios. We construct 8 volume-institutional ownership portfolios in a similar manner.[8] Once portfolios are formed in this manner at the beginning of each month, their composition remains unchanged for the remainder of the month. This two-way sorting

[8] The volume-ranked portfolios are based on the daily average trading turnover of the sample stocks over the previous year before the portfolio formation date (see also Chordia and Swaminathan (2000)).

algorithm assures that stocks included in the same portfolio have similar firm size or trading volume and thus should be similarly traded, so that any differences in trading behavior between the low and high institutional ownership portfolios can be attributed to institutional ownership.[9] Following Statman et al. (2006) and Chuang and Lee (2006), we use a value-weighted basis to calculate the weekly returns and turnover of each portfolio. To alleviate the concern associated with the non-trading problem, any stock with no consecutive trading record for more than one week prior to and after the date of portfolio formation is excluded from the portfolio.

To investigate investors' attitudes toward risk in their trading behavior, we also form three-way sorted portfolios based on size, institutional ownership, and the degree of security risk in the following manner. At the beginning of each month, stocks are first sorted into four quartiles based on their market capitalizations. Within each size quartile, stocks are further sorted into two groups based on their institutional ownership. Then within each size-institutional ownership group, stocks are further sorted into two groups based on their risk indicators. This sorting algorithm generates the 16 size-institutional ownership-risk portfolios, and thus each sample stock is assigned to one of 16 portfolios. The 16 volume-institutional ownership-risk portfolios are constructed in a similar manner. As for

[9] We also consider controlling for other firm characteristics like stock returns, the book-to-market ratio, beta, return variance, and firm-specific risk, when forming the low and high institutional ownership portfolios. Since all conclusions drawn from the results using these portfolios are virtually the same as those reported in the paper, we do not report the results using these portfolios to conserve space.

the risk indicators, we focus on firm-specific risk, since the private information that investors collect is more likely to be firm-specific than market-wide. Following Chuang and Lee (2006), we use two measures of risk: firm-specific risk and return volatility. We utilize the market model to estimate firm-specific risk. These two risk measures are calculated using one-year daily returns prior to the portfolio formation date.

2.3. Detrending trading volume series

As pointed out by Gallant, Rossi, and Tauchen (1992) and others, there is significant evidence of both linear and nonlinear time trends in the trading volume series. Therefore, many empirical studies filter trading volume to achieve stationarity. In the spirit of Gallant et al. (1992), we detrend logged portfolio turnover, taking into account the autocorrelation and calendar effects on portfolio turnover by using the following regression (see also Lo and Wang (2000) and Chuang and Lee (2006)):

$$\begin{aligned}\log(T_{ij,t}) &= \alpha_1 + \alpha_2 t + \alpha_3 t^2 + \alpha_4 DEC1_t + \alpha_5 DEC2_t + \alpha_6 DEC3_t + \alpha_7 DEC4_t \\ &+ \alpha_8 JAN1_t + \alpha_9 JAN2_t + \alpha_{10} JAN3_t + \alpha_{11} JAN4_t + \alpha_{12} MAR_t \\ &+ \alpha_{13} APR_t + \ldots + \alpha_{20} NOV_t + \sum_{l=1}^{L} \beta_{ij,l} \log(T_{ij,t-l}) + e_{ij,t},\end{aligned} \tag{1}$$

where $T_{ij,t}$ denotes the portfolio turnover of portfolio *ij*; $e_{ij,t}$ is the regression error; the variables $DEC1_t$, … , $DEC4_t$ and $JAN1_t$, … , $JAN4_t$ denote weekly indicator variables for the weeks in December and January, respectively; and MAR_t, … , NOV_t denote monthly indicator variables for the months of March through November, respectively. February is omitted to avoid the "dummy trap." The number of lags of the autoregressive terms,

$\log(T_{ij,t-l})$, is determined by the Ljung-Box Q-statistic; that is, we add lags until the Ljung-Box statistic shows no autocorrelation of the residual terms for each detrended portfolio turnover series. The estimated error is denoted by $V_{ij,t}$ and is used as the measure of trading volume for portfolio ij.

2.4. Summary statistics

Table 2 reports the summary statistics on portfolios. Specifically, Panels A, B, and C of Table 2 report the summary statistics on the 8 size-institutional ownership portfolios, 8 volume-institutional ownership portfolios, and the Taiwanese market index, respectively. The first thing to notice from Table 2 is that the mean monthly institutional ownership fraction of each portfolio is far less than 50 percent, which raises concern about whether the Taiwanese stock market is a good one in which to contrast the overconfident trading of individual versus institutional investors. This concern could be partially mitigated by the use of trading turnover as a measure of investors' trading activities. Table 2 shows that the means of weekly turnover of low and high institutional ownership portfolios within each size and volume quartile are quite similar. Moreover, Taiwanese individual investors might not dominate the market so thoroughly. Barber et al. (2009) report that during their sample period, 1995-1999, Taiwanese individual investors place trades that are roughly half the size of those made by each type of Taiwanese institutional investors, though the former's total trading value outnumbers the latter's. To further address this concern, we conduct a subperiod analysis of all our empirical tests in Section 3.6 where the sample is divided into two equal-length sub-samples. The focus is to see whether individual investors still trade more overconfidently than institutional investors during the latter subperiod when institutional investors trade more active in the stock market.

Panel A of Table 2 shows that the market capitalizations of the two portfolios are similar within each size quartile. This shows that there is not a strong relation between size and institutional ownership. Except for the largest size quartile, the mean weekly turnover is higher for the high institutional ownership portfolio than for the low institutional ownership portfolio within the first three size quartiles, a finding consistent with what is observed in the U.S. stock markets (see, for example, Badrinath et al. (1995) and Covrig and Ng (2004)). This finding, however, does not necessarily mean that institutional investors trade more irrationally than individual investors. Higher institutional trading could be motivated from rational motives such as hedging demands, portfolio rebalancing, and liquidity needs. This emphasizes the importance of using the testable implications of the overconfidence hypothesis to explore which type of investors is the more overconfident trader. It is worth noting that trading turnover in the Taiwanese stock market is remarkably high during our sample period. For example, the size-institutional ownership portfolio P_{1l} has a mean weekly turnover of 3.52% (or 182.88% annually). Panel B of Table 2 shows that the mean weekly turnover of the two portfolios is similar within each volume quartile. This indicates that we are successful in reducing the association between volume and institutional ownership. One interesting observation yielded from Panel B of Table 2 is that the market capitalization of the high institutional ownership portfolio is greater than that of the low institutional ownership portfolio within each volume quartile. This observation is consistent with what is observed in the U.S. stock market that institutional investors tend to hold larger stocks, while individual investors tend to hold smaller stocks (see, for example, Badrinath et al. (1995) and Sias and Starks (1997)).

Table 2 also reports the estimated Sharpe ratios for each portfolio. It shows that, with the exception of the volume-institutional ownership portfolios P_{2l} vs. P_{2h}, the high institutional ownership portfolios have a higher Sharpe ratio than the corresponding low institutional ownership portfolios within each size and volume quartile. Following Barber et al. (2009), Table 2 reports abnormal returns for each portfolio for different holding periods: 1 day, 5 days, 10 days, 25 days and 140 days.[10] That is, we generate 40 comparisons between low and high institutional ownership portfolios. With only four exceptions, we find that the estimated abnormal returns are higher for the high institutional ownership

[10] Barber et al. (2008) use the transaction data of all traders on the TSE to form the buy and sell portfolios based on net daily buys and sells of each type of investors and then calculate the monthly abnormal returns on each portfolio as the intercept from a four-factor model. Following their methodology, we first calculate the daily returns on each portfolio, assuming a holding period of 1, 5, 10, 25, or 140 days. Daily returns are then compounded within a month to generate a time series of monthly returns for each portfolio. Finally, the monthly abnormal returns are calculated as the intercept from a time series regression of the portfolio excess returns on the market excess returns, a firm-size factor, a value-growth factor, and a momentum factor. The four factors are constructed as in Barber et al. (2008). Also following their work, we use the one-month deposit rate of the First Commercial Bank as the risk-free rate in calculating the Sharpe ratio and the portfolio and market excess returns. The results are qualitatively similar to what we report in Table 2, if the intercept is calculated from a one-factor model, using the market risk premium as the sole factor or from a three-factor model without a momentum factor.

portfolios.[11] Taken together, these results point out that the trading performance of individual investors is worse than that of institutional investors.

The results of the ADF test show that the null hypothesis of a unit root can be rejected for the detrended log turnover and return series of each portfolio and for the series of the Taiwanese market index, indicating that they are stationary time series. The ARCH LM test strongly suggests the presence of a time-varying second moment for the return series of each portfolio and for that of the Taiwanese market index.

2.5. Preliminary analysis

Shefrin and Statman (1985) propose the disposition effect, where investors are predisposed to holding losers too long and selling winners too soon. Thus, this model also implies a positive linkage between lagged stock returns and current trading volume. Statman et al. (2006) argue that the disposition effect is a stock-specific effect, while the overconfidence hypothesis is a market-wide effect. Specifically, they argue that the disposition effect refers to investors' attitudes toward specific stocks in their portfolios, whereas the overconfidence hypothesis states that overconfident investors exaggerate their ability to increase wealth by actively trading any stocks they can trade rather than specific

[11] Both Panels A and B of Table 2 show that P_{1l}, P_{1h}, P_{2l}, and P_{2h}, on average, tend to have negative abnormal returns at horizons of 1-, 5-, and 10-day holding periods but have positive abnormal returns at the longer horizons of 25- and 140-days holding periods. P_{3l}, P_{3h}, P_{4l}, and P_{4h}, on average, tend to have positive abnormal returns at any holding periods. Although these observations imply that individual investors have opportunities to earn positive abnormal returns at longer holding periods, their preference for short-term trading might make them realize losses rather than profits. As indicated by Barber, Lee, Liu, and Odean (2005), day trading accounts for over 20 percent of trading volume in Taiwan during their sample period from 1995 to 1999, 97.5 percent of which were made by individual investors.

stocks they currently hold. Gervais and Odean (2001) also argue that overconfidence-based trading is a market-wide phenomenon. Accordingly, Statman et al. (2006) interpret a positive relation between past individual security returns and current trading volume as consistent with disposition effect trading and a positive relation between past market returns and current trading volume as consistent with overconfident trading. A similar idea is also explored by Chuang and Lee (2006) in their study on the relation between investors' overconfidence and their risk-taking.

As a preliminary step to study the difference in trading behavior after market gains between individual and institutional investors, we compare the mean weekly portfolio turnover before and after market gains. That is, we calculate 2-, 3-, and 4-week buy-and-hold market returns before the portfolio formation date. If the buy-and-hold market returns are positive, they are further divided into two equal groups –i.e., high and low positive market returns– based on their magnitude.[12] Then we calculate the mean weekly portfolio turnover conditional on these returns. We also form three-way sorted portfolios based on size/volume, institutional ownership, and stock returns as the above size- and volume-institutional ownership-risk portfolios. Similarly, we use 2-, 3-, and 4-week buy-and-hold stock returns before the portfolio formation date as the third sorting criterion

[12] We also use the positive sum of the lagged 2-, 3-, and 4-week market returns as an alternative conditional event and find the similar results.

for the size- and volume-institutional ownership-return portfolios.[13] Then, we calculate the mean weekly turnover for each portfolio.

We perform three tests on the before and after mean turnover statistics. First, we test the null hypothesis that the mean weekly turnover of the size- and volume-institutional ownership portfolios *ij* conditional on past high positive market returns is equal to that conditional on past low positive market returns within each size and volume quartile. That is, we test if portfolio turnover is equal for each size and volume portfolio. We call this test t-1($P_{ij\text{-}hm}=P_{ij\text{-}lm}$).

Second, we test the null hypothesis of the equality of the mean weekly turnover of the low versus high institutional ownership portfolios conditional on past high positive market returns within each size and volume quartile. That is, we examine if the low institutional ownership portfolios trade more after market gains than the high institutional portfolios, or equivalently if individual investors are more prone to overconfident trading than institutional investors. We call this test t-2($P_{il\text{-}hm}=P_{ih\text{-}hm}$). This test is particularly important because more rigorous tests are warranted only if we find the significant difference in trading after market gains between individual and institutional investors. Finally, as a check of our results, we test the null hypothesis that the mean weekly turnover of the low institutional ownership portfolios conditional on past high positive market returns is equal

[13] The results are only slightly changed when the sum of the lagged 2-, 3-, and 4-week stock returns is used as the third sorting criterion.

to that of the high institutional ownership portfolios conditional on past low positive market returns within each size and volume quartile. We call this test t-3($P_{il\text{-}hm}=P_{ih\text{-}lm}$).

Table 3 reports the mean weekly portfolio turnover conditional on past high and low 3-week market returns for two different sorts. Specifically, Panels A and B report the results for the size- and volume-institutional ownership portfolios, respectively.[14]

First, we find that the magnitude of portfolio turnover is always higher after high positive market returns than after low positive market returns. Second, we find that for 13 out of the 16 cases, the t-1($P_{ij\text{-}hm}=P_{ij\text{-}lm}$) test statistic rejects the null hypothesis of equal turnover at the 5% level. That is, on average, we find that both individual and institutional investors are significantly more actively after high market gains than after low market gains.

Third, the t-2($P_{il\text{-}hm}=P_{ih\text{-}hm}$) test statistic strongly rejects the null hypothesis of equal turnover for the low and high institutional ownership portfolios after high positive market. This null hypothesis is rejected in all the cases at the 1% level. That is, individual investors tend to trade more after high market gains than institutional investors, suggesting that individual investors trade with more overconfidence than institutional investors. This is an important result since it provides strong support for the tested hypothesis as well as the basis for further analysis of the overconfident trading behavior of individual versus institutional investors conditional on various events.

[14] We do not report the results of the mean weekly portfolio turnover conditional on 2- and 4-week buy-and-hold market returns since the conclusions drawn from these results are the same as those drawn from Table 3.

Finally, the t-3($P_{il\text{-}hm}$=$P_{ih\text{-}lm}$) test statistic strongly rejects the null hypothesis that the mean weekly turnover of the low institutional ownership portfolios conditional on past high positive market returns is equal to that of the high institutional ownership portfolios conditional on past low positive market returns within each size and volume quartile. We use this test as a check of our overconfidence hypothesis.[15]

Overall, this preliminary analysis presents significant evidence that individual investors tend to trade with higher overconfidence than institutional investors.

3. Empirical frameworks and results

3.1. Causal relation between portfolio volume and market returns

The self-learning model of Gervais and Odean (2001) predicts that biased investors mistakenly attribute market gains to their ability to pick winning stocks and overestimate the quality of the information they gather, and the process of wealth accumulation makes them overconfident; therefore, they trade more aggressively following market gains, implying a positive causality running from returns to volume.[16]

It should be noted that some theories of trading volume share some of the implications of the overconfidence hypothesis regarding the causal relation between returns and volume. For example, the sequential information arrival models of Copeland (1976) and Jennings,

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[15] As a final check, we perform a similar analysis conditioning on past portfolio returns instead of past market returns. The results, though weaker, are consistent with those reported in Table 3.

[16] The causality from trading volume to stock returns is consistent with an old Wall Street saying that "It takes volume to make prices move." This adage was later confirmed empirically by Smirlock and Starks (1985), Harris (1986, 1987), Gallant, Rossi, and Tauchen (1992), and Cooper (1999), among many others.

Starks, and Fellingham (1981) suggest a positive causal relation between returns and volume in either direction, i.e., a feedback relation. To reconcile the difference between the short- and long-run autocorrelation properties of aggregate stock returns, De Long et al. (1990) develop a positive-feedback trading model, implying a positive bi-directional causal relation between returns and volume.[17]

Before introducing our empirical models, we first discuss two control variables used in all our tests. Ross (1989b) shows that in a frictionless market characterized by an absence of arbitrage opportunities, the rate of information flow is revealed by the volatility of asset returns. Based on this intuition, prior studies use the absolute value of market returns to proxy for market-wide information flows and the absolute cross-sectional deviation of individual stock returns from market-model expected returns to proxy for firm-specific information flows (see also Bessembinder, Chan, and Seguin (1996), Covrig and Ng (2004), and Chuang and Lee (2006)). Statman et al. (2006) argue that market volatility and the cross-sectional standard deviation of security returns used in their study are similar to these two control variables and help account for potential trading activity associated with portfolio rebalancing.

The absolute value of market returns is denoted as $|R_{m,t}|$, where $R_{m,t}$ is the return on a

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[17] A positive causal relation from trading volume to stock returns is consistent with the assumption that trading strategies pursued by noise traders cause stock prices to move. A positive causal relation from stock returns to trading volume is also consistent with the positive-feedback trading strategies of noise traders, for which the decision to trade is conditional on past stock price movements.

value-weighted Taiwanese market index, and the mean absolute stock return deviation is defined as follows:

$$MAD_{ij,t} = \sum_{h=1}^{H} w_{hij} \mid R_{hij,t} - \beta_{hij} R_{m,t} \mid, \tag{2}$$

where $R_{hij,t}$ is the return of stock h in portfolio ij, $R_{m,t}$ is the return on a value-weighted Taiwanese market index, β_{hij} is the beta of stock h in portfolio ij estimated using the previous year's daily data, w_{hij} is the (value-weighted) weight of stock h in portfolio ij, and H is the total number of stocks in portfolio ij. We work with a detrended $|R_{m,t}|$ series, since it is well-known that $|R_{m,t}|$ is highly serially correlated (see, for example, Ding, Granger, and Engle (1993)). We also find high serial correlation for $MAD_{ij,t}$, and, consequently, we also detrend the $MAD_{ij,t}$ series. We follow Pagan and Schwert's (1989) method to filter $|R_{m,t}|$ and $MAD_{ij,t}$ by using the following two models:

$$\mid R_{m,t} \mid = \alpha_m + \sum_{p=1}^{P} \beta_{m,p} \mid R_{m,t-p} \mid + e_{m,t}, \tag{3}$$

$$MAD_{ij,t} = \alpha_{ij} + \sum_{q=1}^{Q} \beta_{ij,q} MAD_{ij,t-q} + e_{ij,t}. \tag{4}$$

We take $DAVR_{m,t}$ as the estimated error in equation (3), i.e., $e_{m,t}$, and similarly $DMAD_{ij,t}$ as the estimated error in equation (4), i.e., $e_{ij,t}$, and use them as control variables in our empirical models.[18]

To distinguish between the overconfident trading hypothesis and the alternative trading hypotheses, we use Zellner's (1962) Seemingly Unrelated Regression (SUR) model to

[18] We also reestimate all our empirical models using undetrended $|R_{m,t}|$ and $MAD_{ij,t}$. The results are largely unchanged.

perform the bivariate Granger (1969, 1988) causality tests for each portfolio:

$$V_{ij,t} = \alpha_{ij,1} + \sum_{a=0}^{A} \beta_{ij,11a} DAVR_{m,t-a} + \sum_{b=0}^{B} \beta_{ij,12b} DMAD_{ij,t-b} + \sum_{c=1}^{C} \beta_{ij,13c} R_{ij,t-c} + \sum_{d=1}^{D} \gamma_{ij,11d} V_{ij,t-d} + \sum_{d=1}^{D} \gamma_{ij,12d} R_{m,t-d} + \varepsilon_{ij,1t}, \tag{5}$$

$$R_{m,t} = \alpha_{ij,2} + \sum_{d=1}^{D} \gamma_{ij,21d} V_{ij,t-d} + \sum_{d=1}^{D} \gamma_{ij,22d} R_{m,t-d} + \varepsilon_{ij,2t}, \tag{6}$$

where $V_{ij,t}$ is the detrended trading volume of portfolio *ij*, $R_{m,t}$ is the return on a value-weighted Taiwanese market index, $R_{ij,t}$ is the return of portfolio *ij*, $DAVR_{m,t}$ is the detrended absolute value of market returns, and $DMAD_{ij,t}$ is the detrended mean absolute portfolio return deviation. Portfolio *ij* refers to a portfolio of size *i* and institutional ownership *j*. Specifically, $i = 1, 4$ refers to the smallest and largest size portfolios, respectively, and $j = l, h$ refers to the low and high institutional ownership portfolios, respectively. The volume-institutional ownership portfolios are defined analogously. The number of lags in equations (2) and (3) is chosen by considering both the Akaike (1974) information criterion (AIC) and Schwartz (1978) information criterion (SIC).

The causality between the variables in the SUR model is tested using a Wald test based on the theoretically implied parameter restrictions. In equation (5), for any portfolio *ij* a rejection of the null hypothesis that market returns do not Granger-cause portfolio volume (i.e., $\gamma_{ij,12d} = 0$ for all *d*) and the observation that the sum of the $\gamma_{ij,12d}$ coefficients is significantly positive jointly indicate a positive causality running from market returns to trading volume, which is consistent with the prediction of Gervais and Odean's (2001) overconfident trading hypothesis. In equation (6), for any portfolio *ij* a rejection of the null hypothesis that portfolio volume does not Granger-cause market returns (i.e., $\gamma_{ij,21d} = 0$ for all *d*) and the observation that the sum of the $\gamma_{ij,21d}$ coefficients is significantly positive jointly indicate a positive causality running from portfolio volume to market returns. A positive feedback relation between portfolio volume and market returns provides evidence in favor of either the sequential information arrival model or positive-feedback trading hypotheses or both.

Table 4 reports the results of the Granger causality tests based on the estimation of the bivariate SUR model of equations (5) and (6). To save space, we do not report the estimated coefficients in Table 4 and the following tables. Specifically, Table 4 reports two Wald tests, the *W-D* and *W*-1 statistics, which follows a χ^2 distribution with *D* and 1 degree of freedom, respectively. The *W-D* test statistic is used to test the causality restrictions. When causality exists, we further use the *W*-1 test statistic to test the null hypothesis that the sum of the lagged coefficients is equal to zero to identify the sign of the causality.

Panels A and B of Table 4 report the results for the size-institutional ownership and volume-institutional ownership portfolios, respectively. Both Panels A and B of Table 4 show that the null hypothesis that market returns do not Granger-cause portfolio volume (i.e., $\gamma_{ij,12d} = 0$ for all *d*) is rejected at conventional significance levels for all size-institutional ownership portfolios and all volume-institutional ownership portfolios, respectively. Moreover, the cumulative effect of lagged market returns on portfolio volume measured by the sum of the lagged $\gamma_{ij,12d}$ coefficients is positive and significantly different from zero at conventional significance levels for these portfolios. These findings suggest that market gains help predict the increase in portfolio volume, which is consistent with the prediction of the overconfident trading hypothesis. Both Panels A and B of Table 4 also show that the null hypothesis that portfolio volume does not Granger-cause market returns (i.e., $\gamma_{ij,21d}$ = 0 for all d) cannot be rejected at conventional significance levels for any size-institutional ownership portfolios and any volume-institutional ownership portfolios, respectively. Put together, the results therefore imply no feedback relation between portfolio volume and market returns, which is not consistent with the prediction of the sequential information arrival or the positive feedback trading hypotheses.

3.2. Causal relation across portfolios

After ruling out the alternative trading hypotheses, we run the following bivariate SUR model across the low and high institutional ownership portfolios within each size and within volume quartile to compare the relative degree of the overconfident trading of individual versus institutional investors over the full sample period:

$$V_{ij,t} = \alpha_{ij} + \beta_{ij1} DAVR_{m,t} + \beta_{ij2} DMAD_{ij,t} + \sum_{k=1}^{K} \gamma_{ijk} R_{m,t-k} + \varepsilon_{ij,t},$$

for $j = l$ and h, given $i = 1,\ldots, 4$, (7)

where the variables are defined as above, the subscript j represents the cross-sectional unit of the low and high institutional ownership portfolios within size and volume quartile i, and the subscript t represents the weekly time unit. In equation (7), the number of lags for the right-hand side variables is based on the results of the bivariate Granger causality tests. For example, we use two lags on market returns for the size-institutional ownership portfolios, P_{1l} and P_{1h}, because from the bivariate Granger causality tests we find that the significant impact of past market returns on current portfolio volume is up to two lags among these two portfolios. Similarly, we exclude the lagged independent variables of $DAVR_{m,t}$, $DMAD_{ij,t}$, and $R_{ij,t}$ from equation (7) because we find no significant evidence that portfolio volume is affected by these variables for any portfolios. The same method is applied to other tests in this paper. The main advantage of using the SUR model is that it accounts for the cross-portfolio correlations of the contemporaneous residuals in drawing inferences concerning the regression parameters.

In equation (7), the γ_{ijk} coefficients measure the causal relation between the current volume of portfolio ij and lagged market returns. As a consequence, we use the sum of the γ_{ijk} coefficients to measure the degree of the trading activities of individual and institutional investors following market gains. The greater the sum, the more active investors' trading activity following market gains. Since the γ_{ilk} and γ_{ihk} coefficients measure individual and institutional investors' trading due to past market gains, respectively, if individual investors trade more actively following market gains than institutional investors, we expect to find that $\sum_k \gamma_{ilk} > \sum_k \gamma_{ihk}$, given $i = 1, \ldots, 4$.

It should be noticed that the mean institutional holdings of the high institutional ownership portfolios are far less than 50 percent, as shown in Table 2. This raises another question of whether individual investors' trading due to past market gains also contributes to the observed γ_{ihk} coefficients. If this is true, we will overestimate institutional investors' trading due to past market gains. Given the overestimation of $\sum_k \gamma_{ihk}$, if we find that $\sum_k \gamma_{ilk} > \sum_k \gamma_{ihk}$, given $i = 1, \ldots, 4$, then we can feel confident to say that individual investors do trade more actively following market gains than institutional investors. But if we find that $\sum_k \gamma_{ilk} < \sum_k \gamma_{ihk}$, given $i = 1, \ldots, 4$, then we cannot determine whether institutional investors trade more actively following market gains than individual investors.

In addition to estimating the coefficients, our empirical tests involve the following three steps. In equation (7), for example, we first estimate whether the causal relation from market returns to portfolio volume exists using the W-$K(\gamma)$ test statistic, which follows a χ^2 distribution with K degrees of freedom, to test the null hypothesis that $\gamma_{ijk} = 0$ for all k for each portfolio ij. Then, we observe the sum of lagged coefficients on market returns and estimate the sign of causality in the first step using the W-$1(\gamma)$ test statistic, which follows a χ^2 distribution with one degree of freedom, to test the null hypothesis that $\sum_k \gamma_{ijk} = 0$ for each portfolio ij. The first two steps provide us with the results of whether individual and institutional investors trade overconfidently. Finally, we compare the relative degree of the overconfident trading activity of individual versus institutional investors that is induced by past market gains using the W-1(γ_{il}=γ_{ih}) test statistic, which follows a χ^2 distribution with one degree of freedom, to test the null hypothesis that $\sum_k \gamma_{ilk} = \sum_k \gamma_{ihk}$ for the low and high institutional ownership portfolios within each size and volume quartile.

Table 5 reports the estimation results of the bivariate SUR model of equation (7).[19] Panels A and B of Table 5 present the results for the size- and volume-institutional ownership portfolios, respectively. Both Panels A and B of Table 5 show that that the W-K(γ) test statistic rejects the null hypothesis that γ_{ijk} = 0 for all k at conventional significance levels for all size- and volume-institutional ownership portfolios, respectively. In addition, all estimated γ_{ijk} coefficients are positive, and the W-1(γ) test statistic rejects the null hypothesis that $\sum_k \gamma_{ijk} = 0$ at conventional significance levels for these portfolios. These findings suggest that both individual and institutional investors trade more actively after market gains. Moreover, we find that $\sum_k \gamma_{ilk} > \sum_k \gamma_{ihk}$ and the W-1(γ_{il}=γ_{ih}) test statistic rejects the null hypothesis that $\sum_k \gamma_{ilk} = \sum_k \gamma_{ihk}$ within each size and volume quartile i. These findings support the hypothesis that individual investors tend to trade more actively following market gains than institutional investors.

3.3. Causal relation across portfolios: conditional on market states

[19] Prior studies on trading volume find a positive contemporaneous relation between trading volume and the absolute value of market returns and between trading volume and the mean absolute stock return deviation (e.g., Bessembinder, Chan, and Seguin (1996), Covrig and Ng (2004), and Chuang and Lee (2006)). Consistent with prior studies, in unreported results, we find that all the β_{ij1} and β_{ij2} coefficients are positive and significant at conventional significance levels. These findings indicate a significant positive contemporaneous relation between $V_{ij,t}$ and $DAVR_{m,t}$ and between $V_{ij,t}$ and $DMAD_{ij,t}$ in our portfolios.

An old Wall Street adage, "Don't confuse brains with a bull market," provides investors with the best warning against becoming overconfident during a bull market. Gervais and Odean (2001) argue that overconfident investors are more likely to trade aggressively and speculatively right after a bull market (see also Odean (1998) and Daniel et al. (2001)). This implies that overconfidence is time-varying, which could manifest in investors' trading more actively right after a bull market than at other times. From the standpoint of our empirical framework, this situation further implies that the positive causal relation between current portfolio volume and lagged market returns should be stronger right after a bull market than it is during other states of the market.

To test this empirical implication, we need to define a bull market. However, the determination of a bull market is somewhat subjective. Chuang and Lee (2006) use the periods of NBER-dated expansions as a proxy for bull markets. Similarly, in this paper, we use the economic monitoring indicators released by the Council for Economic Planning and Development (CEPD) in Taiwan to identify the periods of the bull markets.[20] Then, we run the following bivariate SUR model across the low and high institutional ownership

[20] There are nine components in the economic monitoring indicators: monetary aggregate M1B, direct and indirect finance, bank clearings and remittance, stock price, manufacturing new orders (deflated), exports (deflated), industrial production, manufacturing inventory ratio, nonagricultural employment. Each component is scored between 1 to 5 points. The CEPD gives five different lights according to the sum of points. The red light is between 38 to 45 points, meaning that the economy is overheated. The yellow-red light is between 32 to 57 points, meaning the economy transits from stability to overheat. The green light is between 23 to 31 points, meaning that the economy is stable. The yellow-blue light is between 17 to 22 points, meaning that the economy transits from stability to recession. The blue light is between 9 to 16 points, meaning that the economy is recessionary. The red, yellow-red, and green lights are the indicators of expansions in the Taiwan economy, while the yellow-blue and blue lights are the indicators of recessions in the Taiwan economy. For other details about the economic monitoring indicators, please see http://www.cepd.gov.tw/encontent/m.aspx?sNo=0000061.

portfolios within each size and volume quartile over the full sample period:

$$
\begin{aligned}
V_{ij,t} &= \alpha_{ij} + \beta_{ij1} DAVR_{m,t} \times D_t + \beta_{ij2} DAVR_{m,t} \times (1 - D_t) \\
&\quad + \beta_{ij3} DMAD_{i,t} \times D_t + \beta_{ij4} DMAD_{i,t} \times (1 - D_t) \\
&\quad + \sum_{k=1}^{K} \gamma_{ij1k} R_{m,t-k} \times D_{t-k} + \sum_{k=1}^{K} \gamma_{ij2k} R_{m,t-k} \times (1 - D_{t-k}) + \varepsilon_{ij,t},
\end{aligned}
$$

for $j = l$ and h, given $i = 1,\ldots, 4$, (8)

where the variables are defined as above and the dummy variable D_t is meant to capture the state of the market, which is defined in three different ways. In the first case, the dummy variable D_t represents $BU_{g,t}$ and takes on a value of one if week t is included in the period from g weeks after the beginning of CEPD-dated expansion to the end of CEPD-dated expansion and zero otherwise. In the absence of specific guidance from theoretical models regarding the appropriate value of g, we consider four possible values of g, namely g = 1, 2, 3, and 4. This definition of a bull market takes into proper account Gervais and Odean's (2001) argument that market gains make investors trade more actively right after a bull market.

Cooper, Gutierrez, and Hameed (2004) argue that the behavioral theories of Daniel et al. (1998) and Gervais and Odean (2001) jointly imply that an overreaction will be stronger following market gains generating greater momentum in the short-run and find supportive evidence that short-run momentum profits exclusively follow up-markets. As a robustness check, we also follow Cooper et al. (2004) to define up- and down-market states. Cooper et al. (2004) define the up-market state (down-market state) as one whose sum of the lagged three-year market returns is non-negative (negative). In our case, the dummy variable D_t represents $UP_{h,t}$ and takes on a value of one if the sum of the lagged h-week market returns is non-negative and zero otherwise. We consider three possible values of h, namely $h = 4$, 8, and 12. Moreover, we go one step further to argue that investors' overconfident trading should be greater when the market is in up-momentum states than when it is in down-momentum states. To test our argument, we follow Jegadeesh and Titman's (1993, 2002) weighted relative strength strategy, where stocks are weighted by the difference between their past returns and the past returns of an equally weighted index, to construct the momentum indicator. Then the dummy variable D_t represents $WRSS_t$ and takes on a value of one if $WRSS_t \geq 0$ and zero otherwise.[21]

In equation (8), the γ_{ij1k} and γ_{ij2k} coefficients, for example, measure the causal relation between the current volume of portfolio ij and lagged market returns in bull markets and in non-bull markets, respectively. If market gains make investors trade more actively in bull markets than in non-bull markets, we expect to observe that both the γ_{ij1k} and γ_{ij2k} coefficients are positive and that $\sum_k \gamma_{ij1k} > \sum_k \gamma_{ij2k}$ for each portfolio ij. The γ_{il1k} and γ_{ih1k} coefficients, for example, measure the overconfident trading of individual and institutional

[21] It should be noted that if lagged dummy variables are highly correlated with lagged market returns, then equation (8) might just capture the non-linear relationship between past market returns and trading activity. To address this concern, we calculate the correlation between each dummy variable and market returns and find that their correlations fall between -0.0619 and 0.0915. For example, the correlation between $BU_{2,t}$ and $R_{m,t}$ is -0.0188 and between $WRSS_t$ and $R_{m,t}$ is -0.0619. Moreover, we also add $R^2_{m,t-k}$ as an additional regressor in equation (8) and in all the other equations when the dependent variable is portfolio volume and find that it is not statistically significant at all in all cases. Consequently, our interpretation for the empirical results of equation (8) can be free from this concern.

investors after market gains in bull markets, respectively. If, for instance, market gains make individual investors trade more actively in bull markets than institutional investors, we expect to find that $\sum_k \gamma_{il1k} > \sum_k \gamma_{ih1k}$, given $i = 1,\ldots, 4$.

Table 6 reports the estimation results of the bivariate SUR model of equation (8) using the CEPD bull dummy of $BU_{g,t}$, where $g = 2$ and the momentum dummy of $WRSS_t$ for the size-institutional ownership portfolios. We do not report the results using the CEPD bull dummies of $BU_{g,t}$, where $g = 1, 3, 4$ and the up-market state dummies of $UP_{h,t}$, where $h = 4$, 8, 12 in Table 6 because the results based on these three CEPD bull and three up-market state dummies are qualitatively similar to the ones reported for $BU_{2,t}$ and $WRSS_t$, respectively. Moreover, we do not report the results for the volume-institutional ownership portfolios because the conclusions drawn from them are similar to those drawn from the size-institutional ownership portfolios. Specifically, Table 6 reports the W-1(γ_1=γ_2) test statistic, which follows a χ^2 distribution with one degree of freedom, used to test the null hypothesis that $\sum_k \gamma_{ij1k} = \sum_k \gamma_{ij2k}$ for each portfolio ij and the W-1(γ_{il1}=γ_{ih1}) test statistic, which follows a χ^2 distribution with one degree of freedom the relative degree of the trading activity of individual versus institutional investors in bull markets by testing the null hypothesis that $\sum_k \gamma_{il1k} = \sum_k \gamma_{ih1k}$ for the low and high institutional ownership portfolios within each size quartile.

Panel A of Table 6 presents the results using $BU_{2,t}$ for the low and high institutional ownership portfolios within each size quartile. It shows that both $\sum_k \gamma_{ij1k}$ and $\sum_k \gamma_{ij2k}$ are positive and that $\sum_k \gamma_{ij1k} > \sum_k \gamma_{ij2k}$ for all portfolios. The W-1(γ_1=γ_2) test statistic rejects the null hypothesis that $\sum_k \gamma_{ij1k} = \sum_k \gamma_{ij2k}$ at conventional significance levels for P_{1l}, P_{1h}, P_{2l}, P_{2h}, and P_{3l}. These findings suggest that some individual and institutional investors tend to trade more actively in small and medium size stocks subsequent to market gains in bull markets than in non-bull markets, whereas their trading in large size stocks exhibits no significant difference across bull and non-bull markets. For the trading behavior of individual versus institutional investors in bull markets, the results show that $\sum_k \gamma_{il1k} > \sum_k \gamma_{ih1k}$ and that the W-1(γ_{l1}=γ_{h1}) test statistic rejects the null hypothesis that $\sum_k \gamma_{il1k} = \sum_k \gamma_{ih1k}$ at the 5% level for the low and high institutional ownership portfolios within each size quartile i. These findings thus suggest that individual investors tend to trade more actively subsequent to market gains in bull markets than institutional investors.

Panel B of Table 6 presents the results using $WRSS_t$ for the low and high institutional ownership portfolios within each size quartile. It shows that both $\sum_k \gamma_{ij1k}$ and $\sum_k \gamma_{ij2k}$ $\sum_k \gamma_{ij2k}$ are positive and that $\sum_k \gamma_{ij1k} > \sum_k \gamma_{ij2k}$ for all portfolios. The null hypothesis that $\sum_k \gamma_{ij1k} = \sum_k \gamma_{ij2k}$ is rejected at conventional significance levels, based on the W-1(γ_1=γ_2) test statistic, for P_{1l}, P_{1h}, P_{3l}, and P_{4l}. These findings suggest that some individual investors and few institutional investors tend to trade more actively after market gains when the market is in up-momentum states than when it is in down-momentum states.

As to the trading behavior of individual versus institutional investors in up-momentum market states, the results show that $\sum_k \gamma_{il1k} > \sum_k \gamma_{ih1k}$ and that the W-1(γ_{il1}=γ_{ih1}) test statistic rejects the null hypothesis that $\sum_k \gamma_{il1k} = \sum_k \gamma_{ih1k}$ at the 5% level for the low and high institutional ownership portfolios within each size quartile i. These findings therefore suggest that individual investors tend to trade more actively after market gains in up-momentum market states than institutional investors.

3.4. Causal relation across portfolios: conditional on market volatility

Predicting the future price movements in the stock market is not an easy job for any investors, especially when the market is more volatile. Griffin and Tversky (1992) argue that when predictability is very low, professionals tend to be more overconfident than novices and amateurs. In addition to the implication that institutional investors tend to be more overconfident traders than individual investors, their argument also implies that institutional investors will trade more actively following market gains when the market is more volatile with lower predictability than individual investors. However, whether or not investors trade more actively when the market is more volatile is not clear from the finance literature. Theoretical behavioral finance models reach a conclusion that overconfident investors make the market more volatile (e.g., Beons (1998), Daniel et al. (1998), Odean (1998), Wang (1998), Gervais and Odean (2001), and Scheinkman and Xiong (2003)). This implies that investors' overconfident trading increases market volatility, but not vice versa.

Chuang and Lee (2006) and Darrat, Zhong, and Cheng (2007) find evidence in support of this implication. On the other hand, psychological studies find that overconfidence increases with the difficulty of the task (e.g., Lichtenstein and Fischhoff (1977) and Lichtenstein, Fischhoff, and Phillips (1982)). This implies that investors would trade more actively when the market is more volatile than when it is less volatile.

To more directly test Griffin and Tversky's (1992) argument, we begin by estimating the conditional market volatility using the GJR-GARCH(1, 1) model, proposed by Glosten, Jagannathan, and Runkle (1993), in which monthly dummies are included to the conditional mean equation to control for the seasonal effect on market returns.[22] When the conditional market volatility falls in the top (bottom) 30% of its distribution, the market is defined as the high-volatility (low-volatility) state. Then we estimate the following bivariate SUR model across the low and high institutional ownership portfolios within each size and volume quartile over the full sample period:

$$\begin{aligned} V_{ij,t} = {} & \alpha_{ij} + \beta_{ij1} DAVR_{m,t} + \beta_{ij2} DAVR_{m,t} \times HV_t + \beta_{ij3} DAVR_{m,t} \times LV_t \\ & + \beta_{ij4} DMAD_{i,t} + \beta_{ij5} DMAD_{i,t} \times HV_t + \beta_{ij6} DMAD_{i,t} \times LV_t \\ & + \sum_{k=1}^{K} \gamma_{ij1k} R_{m,t-k} + \sum_{k=1}^{K} \gamma_{ij2k} R_{m,t-k} \times HV_{t-k} + \sum_{k=1}^{K} \gamma_{ij3k} R_{m,t-k} \times LV_{t-k} + \varepsilon_{ij,t}, \end{aligned}$$

for $j = l$ and h, given $i = 1,\ldots, 4$, (9)

[22] We use the GARCH framework to estimate market volatility since, in Table 2, we find evidence of the time-varying variance of market returns. Moreover, we also use Nelson's (1991) Exponential GARCH (EGARCH) specification to model the variance and use squared market returns and the absolute value of market returns as a measure of market volatility and find that the conclusions drawn from the EGARCH model and two alternative measures are essentially the same as those reported in the paper.

where the variables are defined as above and the dummy variable HV_t (LV_t) takes on a value of one when the market is in the high-volatility (low-volatility) state and zero otherwise.

In equation (9), the γ_{ij1k} coefficients measure the causal relation between the current volume of portfolio *ij* and lagged market returns in medium-volatility market states, while the γ_{ij1k} and γ_{ij2k} (γ_{ij1k} and γ_{ij3k}) coefficients measure the similar causal relation in high-volatility (low-volatility) market states. In other words, the positive (negative) γ_{ij2k} and γ_{ij3k} coefficients measure the increment (decrement) of the impacts of lagged market returns on the current volume of portfolio *ij* in high- and low-volatility market states, respectively, relative to in medium-volatility market states. If market gains make institutional investors trade more aggressively in high-volatility market states than individual investors, we expect to find that $\sum_k \gamma_{il1k} + \sum_k \gamma_{il2k} < \sum_k \gamma_{ih1k} + \sum_k \gamma_{ih2k}$, given i = 1,…, 4. Moreover, by observing the magnitude of $\sum_k \gamma_{ij2k}$ ($\sum_k \gamma_{ij2k}$) and test the null hypothesis of $\sum_k \gamma_{ij2k} = 0$ ($\sum_k \gamma_{ij2k} = 0$), we can infer whether individual and institutional investors trade more actively in high-volatility (low-volatility) market states, relative to in medium-volatility market states.

Table 7 reports the estimation results of the bivariate SUR model of equation (9). Specifically, Panels A and B of Table 7 present the results for the size- and volume-institutional ownership portfolios, respectively.[23] In Table 7, the W-$K(\gamma_a)$ test

[23] In unreported results, Panels A and B of Table 6 show that the γ_{ij23} and γ_{ij33} coefficients are not statistically significant at all for P_{3l} and P_{3h} and for P_{3l} , P_{3h}, P_{4l} , and P_{4h}, respectively. As a consequence, we also estimate

statistic, which follows a χ^2 distribution with K degrees of freedom, is used to the null hypothesis that γ_{ijak} = 0, for all k and a = 1, 2, and 3 (i.e., in medium-, high-, and low-volatility market states respectively) for each portfolio ij. The W-1(γ_a) test statistic, which follows a χ^2 distribution with one degree of freedom, is used to test the null hypothesis that $\sum_k \gamma_{ijak} = 0$ for a = 1, 2, and 3 for each portfolio ij. Panel A of Table 7 shows that the W-K(γ_1) test statistic rejects the null hypothesis at conventional significance levels for P_{1l}, P_{1h}, P_{2l}, P_{2h}, and P_{3l} and that $\sum_k \gamma_{ij1k} > 0$ and the W-1(γ_1) test statistic rejects the null hypothesis at conventional significance levels for these portfolios. Put together, these findings indicate that some individual and institutional investors trade more actively after market gains in medium-volatility market states. Panel B of Table 7 shows that the W-K(γ_1) test statistic rejects the null hypothesis at conventional significance levels for P_{1l}, P_{2l}, P_{3l}, and P_{4l} and that $\sum_k \gamma_{ij1k} > 0$ and the W-1(γ_1) test statistic rejects the null hypothesis at conventional significance levels for these portfolios. Taken together, these findings indicate that only individual investors trade more actively after market gains in medium-volatility market states.

Looking at the results of when the market is in the high-volatility state, we find that the W-K(γ_2) test statistic can not reject the null hypothesis at conventional significance levels for all portfolios in both Panels A and B of Table 7. This signifies that both individual and

equation (9) up to two lags on market returns for these portfolios and find that all conclusions about these portfolios remain unchanged using shorter lags on market returns.

institutional investors do not trade more actively after market gains in high-volatility market states, relative to in medium-volatility market states. On the contrary, in all but one case of the size-institutional ownership portfolio P_{2h}, both Panels A and B of Table 7 show that the W-$K(\gamma_3)$ test statistic rejects the null hypothesis at conventional significance levels for all portfolios and that $\sum_k \gamma_{ij3k} > 0$ and the W-$1(\gamma_3)$ test statistic rejects the null hypothesis at conventional significance levels for these portfolios. These findings signify that both individual and institutional investors trade more actively after market gains in low-volatility market states, relative to in medium-volatility market states.

The results above seem to imply that both individual and institutional investors trade more actively after market gains in low-volatility market states than in high-volatility market states. To provide evidence on this observation, we formally test whether individual and institutional investors trade more actively after market gains in low-volatility market states than in high-volatility market states by comparing the magnitudes of $\sum_k \gamma_{ij1k} + \sum_k \gamma_{ij2k}$ versus $\sum_k \gamma_{ij1k} + \sum_k \gamma_{ij3k}$, which is equivalent to comparing the magnitude of $\sum_k \gamma_{ij2k}$ versus $\sum_k \gamma_{ij3k}$, and testing the null hypothesis of $\sum_k \gamma_{ij1k} + \sum_k \gamma_{ij2k} = \sum_k \gamma_{ij1k} + \sum_k \gamma_{ij3k}$ based on the W-$1(\gamma_1+\gamma_2=\gamma_1+\gamma_3)$ test statistic, which follows a χ^2 distribution with one degree of freedom. Both Panels A and B of Table 7 show that $\sum_k \gamma_{ij2k} < \sum_k \gamma_{ij3k}$ for all size- and volume-institutional ownership portfolios and that the W-$1(\gamma_1+\gamma_2=\gamma_1+\gamma_3)$ test statistic rejects the null hypothesis at conventional significance levels for these portfolios. These findings indicate that both individual and institutional investors trade more actively after market gains in low-volatility market states than in high-volatility market states, which is inconsistent with the finding of psychological studies that overconfidence is greater when people undertake difficult tasks.

To determine which type of investors trade more aggressively after market gains in high-volatility market states, we compare the magnitudes of $\sum_k \gamma_{il2k}$ versus $\sum_k \gamma_{ih2k}$ and test the null hypothesis of $\sum_k \gamma_{il2k} = \sum_k \gamma_{ih2k}$ based on the W-1(γ_{il2}=γ_{ih2}) test statistic, which follows a χ^2 distribution with one degree of freedom, for the low and high institutional ownership portfolios within each size and volume quartile i. Panels A and B of Table 7 show that $\sum_k \gamma_{il2k} > \sum_k \gamma_{ih2k}$ and the W-1(γ_{il2}=γ_{ih2}) test statistic rejects the null hypothesis at conventional significance levels in the cases of P_{1l} versus P_{1h} and P_{4l} versus P_{4h} and in the cases of P_{2l} versus P_{2h} and P_{3l} versus P_{3h}, respectively. These findings provide some evidence that individual investors trade more aggressively after market gains in high-volatility market states than institutional investors, which is inconsistent with the implication of Griffin and Tversky's (1992) argument.

3.5. Causal relation across portfolios: conditional on the risk level of stocks

Psychologists have found that people are prone to take on more risk than expected in many experimental contexts (see, for example, Alpert and Raiffa (1982)). Financial economists have modeled overconfidence as an overestimation of the precision of private information. These theoretical models predict that if investors are overconfident, they hold positions that are riskier than if they were rational. In other words, investors, if overconfident, tend to trade more in riskier securities. Since private information is more likely to be firm-specific than about the market as a whole, it should follow that investors tend to overestimate their ability to predict firm-specific risk. Following Chuang and Lee (2006), we use two risk measures: firm-specific risk and return volatility.

To investigate whether investors underestimate risk in making their investment decisions and trade more in riskier securities as a result of their overconfidence, we estimate the following multivariate SUR model across the four institutional ownership-risk portfolios within each size and volume quartile over the full sample period:

$$V_{ijs,t} = \alpha_{ijs} + \beta_{ijs1} DAVR_{m,t} + \beta_{ijs2} DMAD_{ijs,t} + \sum_{k=1}^{K} \gamma_{ijsk} R_{m,t-k} + \varepsilon_{ijs,t},$$

for j, $s = l$ and h, for every $i = 1,\ldots, 4$, (11)

where $V_{ijs,t}$ is the value-weighted detrended trading volume of portfolio *ijs*, $DMAD_{ijs,t}$ is the detrended value-weighted average of the beta-adjusted differences between the returns of stocks in portfolio *ijs* and the return on a value-weighted Taiwanese market index, and other variables are defined as above. Specifically, portfolio *ijs* refers to a value-weighted portfolio of size i, institutional ownership j, and firm-specific risk level s. As before, $i = 1, 4$ refer to the smallest and largest size portfolios, respectively, and $j = l$, h refer to the low and high institutional ownership portfolios, respectively. $s = l$, h refer to the lowest and highest firm-specific risk portfolios, respectively, within each size- and volume-institutional ownership group ij.

In equation (11), the γ_{ijlk} and γ_{ijhk} coefficients measure the causal relation between the current volume of the least risky portfolio ijl and lagged market returns and that between the current volume of the riskiest portfolio ijh and lagged market returns, respectively, within each size- and volume-institutional ownership group ij. If we observe that $\sum_k \gamma_{ijlk} > \sum_k \gamma_{ijhk}$, then investors trade more in riskier securities subsequent to market gains. The γ_{ilhk} and γ_{ihhk} coefficients measure individual and institutional investors' trading in the riskiest securities subsequent to market gains, respectively, within each size and volume quartile i. If, for example, individual investors trade more in riskier securities subsequent to market gains than institutional investors, we expect to observe that $\sum_k \gamma_{ilhk} > \sum_k \gamma_{ihhk}$, given $i = 1,\ldots, 4$.

Table 8 reports the estimation results of the multivariate SUR model of equation (11). We only report the results using firm-specific risk as a measure of risk for the size-institutional ownership-risk portfolios, since the results using return volatility as a measure of risk and the results of the volume-institutional ownership-risk portfolios are very similar to those reported here. In Table 8, the W-$K(\gamma_{ijs})$ test statistic, which follows a χ^2 distribution with K degrees of freedom and is used to test the null hypothesis that $\gamma_{ijsk} = 0$, for all k and the W-$1(\gamma_{ijs})$ statistic, which follows a χ^2 distribution with one degree of freedom and is used to test the null hypothesis that $\sum_k \gamma_{ijsk} = 0$. Based on the joint results of the W-$K(\gamma_{ijs})$ test statistic, $\sum_k \gamma_{ijsk}$, and the W-1(γ_{ijs}) statistic, investors trade more aggressively in more or less risky securities after market gains in all but three cases (P_{4ll}, P_{4hl}, and P_{4hh}).

Comparing the magnitudes of $\sum_k \gamma_{ijlk}$ and $\sum_k \gamma_{ijhk}$ within each size-institutional ownership group ij, we find that $\sum_k \gamma_{ijlk} > \sum_k \gamma_{ijhk}$ for all cases, with two exceptions in the cases of P_{3hl} versus P_{3hh} and P_{4hl} versus P_{4hh}. Table 8 also reports the W-1$(\gamma_{ijl}=\gamma_{ijh})$ test statistic, which follows a χ^2 distribution with one degree of freedom and is used to test the null hypothesis that $\sum_k \gamma_{ijlk} = \sum_k \gamma_{ijhk}$ within each size-institutional ownership group ij. This null hypothesis is rejected at the 5% level in the cases of P_{1ll} versus P_{1lh}, P_{2ll} versus P_{2lh}, P_{3ll} versus P_{3lh}, and P_{4ll} versus P_{4lh}. Taken together, these findings suggest that only individual investors trade more in riskier securities after market gains than in less risky securities and that institutional investors maintain the same attitude toward the risk level of securities in which they trade before and after market gains.

To see which type of investor trades more in riskier securities after market gains, we compare the magnitudes of $\sum_k \gamma_{ilhk}$ and $\sum_k \gamma_{ihhk}$ within each size quartile i. We find that $\sum_k \gamma_{ilhk} > \sum_k \gamma_{ihhk}$ for the low and high institutional ownership portfolios within each size quartile i. Moreover, the W-1$(\gamma_{ilh}=\gamma_{ihh})$ test statistic, which follows a χ^2 distribution with one degree of freedom and is used to test the null hypothesis that $\sum_k \gamma_{ilhk} = \sum_k \gamma_{ihhk}$, rejects the null hypothesis at the 10% level for the low and high institutional ownership portfolios within each size quartile *i*. Taken together, these findings present evidence that individual investors trade more in riskier securities after market gains than do institutional investors.

3.6. Subsample analysis

A major concern behind our empirical analysis is that individual investors are major participants in the Taiwanese stock market and, thus, dominate the market. During the second part of our sample, institutional trading grows from 15.6% to over 30%. We divide the sample into two equal parts: 1996-2001 and 2002-2008. Then, in each sample, we conduct all our empirical tests.[24]

In general, the subsample results are consistent with our whole sample results. Following our methodology, we are able to generate 64 comparisons between low and high institutional ownership portfolios. With only seven exceptions, the results are the same as in the whole sample analysis. The specific differences from our whole sample results are as follows. First, in Table 5, there is no significant trading difference during the first part of the sample for the volume-institutional ownership portfolios P_{1l} vs. P_{1h} and P_{2l} vs. P_{2h}. Second, for the subsample analysis of Table 6, there is no significant trading difference during the first part of the sample in the case of size-institutional ownership portfolios P_{3l} vs. P_{3h}. That is, for the third size-institutional ownership portfolio, we find that individual investors do

[24] To conserve space, the results are not presented.

not trade more overconfidently in bull markets than institutional investors in the first part of the sample. Third, for the subsample analysis of Table 7, there is no significant trading difference during the first part of the sample in the case of the largest size-institutional ownership portfolios –i.e., P_{4l} vs. P_{4h}– and during the second part of the sample in the case of the smallest size-institutional ownership portfolios –i.e, P_{1l} vs. P_{1h}. Finally, for the subsample analysis of Table 8, there is no significant trading difference during the first part of the sample in the case of the smallest size-institutional ownership portfolios –i.e., P_{1hl} vs. P_{1hh}– and during the second part of the sample in the case of the second quartile size-institutional ownership portfolios –i.e, P_{2lh} vs. P_{2hh}. That is, there is no significant overconfident trading in riskier securities for the size-institutional ownership portfolios P_{1lh} vs. P_{1hh} in the first period and P_{2lh} vs. P_{2hh} in the second period.

From these results, we find that the evidence that individual investors are more overconfident traders than institutional investors is, on average, weaker in the first period than in the second period. This may be due to the fact that the participation of institutional investors in the Taiwanese stock market is substantially lower in the first period.[25] But, overall, our conclusion that individual investors are more overconfident traders than institutional investors still holds.

[25] We find that the difference in the mean monthly institutional ownership fractions between the low and high institutional ownership portfolios within each size and volume quartile is smaller in the first subperiod than in the second subperiod.

4. Concluding remarks

In this paper, we investigate the trading behavior of individual versus institutional investors in Taiwan from various perspectives of Gervais and Odean’s (2001) overconfident trading hypothesis in an attempt to comprehensively evaluate which type of investors are the more overconfident traders. To this end, we form the size- and volume-institutional ownership portfolios that are different in terms of institutional ownership but similar in terms of firm size and trading volume, respectively, and the size- and volume-institutional ownership-risk portfolios in which the institutional ownership-risk portfolios that have the similar degree of institutional ownership but vary in the degree of risk within each size and volume quartile, respectively. Then, we conduct the bivariate Granger causality tests of portfolio volume and market returns for each size- and volume-institutional ownership portfolios, the various bivariate SUR analyses of the lead-lag relation between current portfolio volume and lagged market returns across the low and high institutional ownership portfolios within each size and volume quartile, and the multivariate SUR analysis of the same lead-lag relation across the institutional ownership-risk portfolios within each size and volume quartile.

The results of the bivariate Granger causality tests show that there is a significant positive causal relation between current portfolio volume and lagged market returns in all portfolios. Also, we find no evidence that there is a positive feedback relation between portfolio volume and market returns for these portfolios. As such, we can rule out the possibility that the observed positive causal relation between current portfolio volume and lagged market returns is due to either the sequential information arrival model or the positive feedback trading hypothesis or both. Moreover, the results of the bivariate SUR model show that the positive causal relation between current portfolio volume and lagged market returns is stronger for the portfolios with low institutional ownership than for the portfolios with high institutional ownership. That is, we find evidence showing that market gains make individual investors trade more actively in subsequent periods than institutional investors.

Behavioral finance theory suggests that investors' overconfident trading is more pronounced during bull markets, up-market states, and up-momentum market states, and when they underestimate risk. We examine the trading behavior of individual versus institutional investors conditional on these events. Consistent with the predictions of the behavioral finance theory, we find evidence that both individual and institutional investors tend to trade more aggressively after market gains during bull markets, up-state markets, and up-momentum market states and that only individual investors trade more in riskier securities after market gains. Conditional on market volatility, we also find that both individual and institutional investors trade more aggressively after market gains in low-volatility market states than in high-volatility market states.

Finally, we compare the relative degree of the trading activity of individual versus institutional investors subsequent to market gains conditional on these events. First, we find that market gains make individual investors trade more actively in subsequent periods during bull markets, up-state markets, and up-momentum market states than institutional investors. Second, we find that market gains make individual investors trade more actively in subsequent periods in high-volatility market states than institutional investors. Third, market gains make individual investors trade more in riskier securities in subsequent periods than institutional investors.

Overall, we provide extensive evidence that individual investors display more significant overconfident trading behavior in various situations and, as a result, are more overconfident traders than institutional investors. These findings are consistent with Gervais and Odean's (2001) argument that inexperienced individual investors tend to be more overconfident traders than more experienced institutional investors. Our empirical evidence, however, is inconsistent with Griffin and Tversky's (1992) argument that professionals may even be more overconfident than amateurs. In addition, overconfidence has been advanced as an explanation for the excessive trading volume observed in securities markets. In the Taiwanese stock market, the majority of investors are individual investors. Overall, we find that individual investors' overconfident trading helps explain the high turnover rates observed in the Taiwanese stock market.

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References

Akaike, H., 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control 19, 716-723.

Alpert, M., Raiffa, H., 1982. A progress report on the trading of probability assessors. In: Kahneman, D., Slovic, P., Tversky, A. (Eds.), Judgment under uncertainty: Heuristics and Biases. Cambridge University Press, Cambridge.

Badrinath, S. G., Kale, J. R., Noe, T. H., 1995. Of shepherds, sheep, and the cross-autocorrelations in equity returns. Review of Financial Studies 8, 401-430.

Bailey, W., Cai, J., Cheung, Y. L., Wang, F., 2009. Stock returns, order imbalances, and commonality: Evidence on individual, institutional, and proprietary investors in China. Journal of Banking and Finance 33, 9-19.

Barber, B. M., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance 55, 773-806.

Barber, B. M., Odean, T., 2002. Online investors: Do the slow die first? Review of Financial Studies 15, 455-487.

Barber, B. M., Lee, Y. T., Liu, Y. J., Odean, T., 2005. Do individual day traders make money? Evidence from Taiwan. Working paper, University of California, Davis.

Barber, B. M., Lee, Y. T., Liu, Y. J., Odean, T., 2007. Is the aggregate investor reluctant to realise losses? Evidence from Taiwan. European Financial Management 13, 423-447.

Barber, B. M., Lee, Y. T., Liu, Y. J., Odean, T., 2009. Just how much do individual investors lose by trading? Review of Financial Studies 22, 609-632.

Benos, A. V., 1998. Aggressiveness and survival of overconfident traders. Journal of Financial Markets 1, 353-383.

Bessembinder, H., Chan, K., Seguin, P. J., 1996. An empirical examination of information, differences of opinion, and trading activity. Journal of Financial Economics 40, 105-134.

Biais, B., Hilton, D., Mazurier, K., Pouget, S., 2005. Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market. Review of Economic Studies 72, 287-312.

Caballé, J., Sákovics, J., 2003. Speculating against an overconfident market. Journal of Financial Markets 6, 199-225.

Chordia, T., Swaminathan, B., 2000. Trading volume and cross-autocorrelations in stock returns. Journal of Finance 55, 913-935.

Chuang, W. I., Lee, B. S., 2006. An empirical evaluation of the overconfidence hypothesis. Journal of Banking and Finance 30, 2489-2515.

Cooper, M., 1999. Filter rules based on price and volume in individual security overreaction. Review of Financial Studies 12, 901-935.

Cooper, M. J., Gutierrez, R. C., Hameed, A., 2004. Market states and momentum. Journal of Finance 59, 1345-1365.

Copeland, T. E., 1976. A model of asset trading under the assumption of sequential information arrival. Journal of Finance 31, 1149-1168.

Covrig, V., Ng, L., 2004. Volume autocorrelation, information, and investor trading. Journal of Banking and Finance 28, 2155-2174.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839-1886.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 2001. Overconfidence, arbitrage, and equilibrium asset pricing. Journal of Finance 56, 921-965.

Darrat, A. F., Zhong, M., Cheng, L. T. W., 2007. Intraday volume and volatility relations with and without public news. Journal of Banking and Finance 31, 2711-2729.

Deaves, R., Lüders, E., Luo, G. Y., 2009. An experimental test of the impact of overconfidence and gender on trading activity. Review of Finance 13, 555-575.

De Bondt, W., Thaler, R., 1995. Financial decision making in markets and firms: A behavior perspective. In: Jarrow, R. A., Maksimovic, V., and Ziemba, W. T. (Eds.), Handbooks in Operations Research and Management Science, Vol. 9, Finance, pp. 383-410.

De Long, J. B., Shleifer, A., Summers, L., Waldmann, R. J., 1990. Positive feedback investment strategies and destabilizing speculation. Journal of Finance 45, 379-395.

De Long, J. B., Shleifer, A., Summers, L., Waldmann, R. J., 1991. The survival of noise traders in financial markets. Journal of Business 64, 1-20.

Dickey, D. A., Fuller, W. A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74, 427-431.

Ding, Z, Granger, C. W. J., Engle, R. F., 1993. A long memory property of stock market returns and a new model. Journal of Empirical Finance 1, 83-106.

Fuller, W. A., 1976. Introduction to statistical time series. New York: Wiley.

Gallant, A.R., Rossi, P. E., Tauchen, G., 1992. Stock prices and volume. Review of Financial Studies 5, 199-242.

Gervais, S., Odean, T., 2001. Learning to be overconfident. Review of Financial Studies 14, 1-27.

Glaser, M., Weber, M., 2007. Overconfidence and trading volume. Geneva Risk and Insurance Review 32, 1-36.

Glosten, L. R., Jagannathan, R., Runkle, D., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779-1801.

Granger, C. W. J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, 424-438.

Granger, C. W. J., 1988. Some recent developments in a concept of causality. Journal of Econometrics 39, 199-211.

Griffin, D., Tversky, A., 1992. The weighting of evidence and the determinants of overconfidence. Cognitive Psychology 24, 411-435.

Harris, L., 1986. Cross-security tests of the mixture of distributions hypothesis. Journal of Financial and Quantitative Analysis 21, 39-46.

Harris, L., 1987. Transactions data tests of the mixture of distributions hypothesis. Journal of Financial and Quantitative Analysis 22, 127-142.

Hirshleifer, D., Luo, G. T., 2001. On the survival of overconfident traders in a competitive securities market. Journal of Financial Markets 4, 73-84.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65-91.

Jegadeesh, N., Titman, S., 2002. Cross-sectional and time series determinants of momentum returns. Review of Financial Studies 15, 143-157.

Jennings, R., Starks, L., Fellingham, J., 1981. An equilibrium model of asset trading with sequential information arrival. Journal of Finance 36, 143-161.

Kyle, A. S., Wang, F. A., 1997. Speculation duopoly with agreement to disagree: Can overconfidence survive the market test? Journal of Finance 52, 2073-2090.

Lichtenstein, S., Fischhoff, B., 1977. Do those who know more also know more about how much they know? Organizational Behavior and Human Performance 20, 159-183.

Lichtenstein, S., Fischhoff, B., Phillipes, L., 1982. Calibration of probabilities: The state of the art to 1980; in Daniel Kahneman, Paul Slovic, and Amos Tversky, eds.: Judgment Under Uncertainty: Heuristics and Biases, Cambridge University Press, Cambridge and New York.

Lo, A. W., Wang, J., 2000. Trading volume: Definition, data analysis, and implications of portfolio theory. Review of Financial Studies 13, 257-300.

Nelson, D. B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347-370.

Odean, T., 1998. Volume, volatility, price, and profit when all traders are above average. Journal of Finance 53, 1887-1934.

Odean, T., 1999. Do investors trade too much? American Economic Review 89, 1279-1298.

Pagan, A. R., Schwert, G. W., 1990. Alternative models for conditional stock volatility. Journal of Econometrics 45, 267-290.

Ross, S. A., 1989a. Discussion: Intertemporal Asset Pricing. In Theory of valuation: Frontiers of Modern Financial Theory, edited by Sudipto Bhattacharya and George M. Constantinides. Totowa, N.J.: Rowman and Littlefield.

Ross, S., 1989b. Information and volatility: The no-Arbitrage martingale approach to timing and resolution irrelevancy. Journal of Finance 44, 1-18.

Rubin, A., 2007. Ownership level, ownership concentration and liquidity. Journal of Financial Markets 10, 219-248.

Scheinkman, J. A., Xiong, W., 2003. Overconfidence and speculative bubbles. Journal of Political Economy 111, 1183-1219.

Schwarz, G., 1978. Estimating the dimension of a model, Annals of Statistics 6, 461-464.

Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. Journal of Finance 40, 777-791.

Sias, R. W., 2004. Institutional herding. Review of Financial Studies 17, 165-206.

Sias, R. W., Starks, L. T., 1997. Return autocorrelation and institutional investors. Journal of Financial Economics 46, 103-131.

Smirlock, M., Starks, L., 1985. A further examination of stock price changes and transactions volume. Journal of Financial Research 8, 217-225.

Statman, M, Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Review of Financial Studies 19, 1531-1565.

Von Holstein, S., 1972. Probabilistic forecasting: an experiment related to the stock market. Organizational Behavior and Human Performance 8, 139-158.

Wang, F. A., 1998. Strategic trading, asymmetric information and heterogeneous prior beliefs. Journal of Financial Markets 1, 321-352.

Wang, F. A., 2001. Overconfidence, investor sentiment, and evolution. Journal of Financial Intermediation 10, 138-170.

Yates, J. F., Lee, J. W., Bush, J. G., 1997. General knowledge overconfidence: Cross-national variations, response style, and "reality." Organizational Behavior and Human Decision Process 70, 87-94.

Yates, J. F., Lee, J. W., Shinotsuka, H., 1996. Beliefs about overconfidence, including its cross-national variation. Organizational Behavior and Human Decision Process 65, 138-147.

Zellner, A., 1962. An efficient method for estimating seemingly unrelated regressions and tests for aggregate bias. Journal of the American Statistical Association 57, 348-368.

Table 1
Trading Volume by Investor Type on the Taiwan Stock Exchange

This table reports the trading value in amount and in percentage by investor type in the Taiwan Stock Exchange (TSE) from 1996 to 2007. The data source is from the TSE.

	Individual investors				Institutional investors			
	Domestic		Foreign		Domestic		Foreign	
Year	Amount (NT$ billion)	Percentage (%)	Amount (NT$ billion)	Percentage (%)	Amount (NT$ billion)	Percentage (%)	Amount (NT$ billion)	Percentage (%)
1996	23,445.16	89.3	2.67	0.0	2,265.43	8.6	556.73	2.1
1997	68,428.21	90.7	10.85	0.0	5,694.86	7.6	1,289.02	1.7
1998	53,480.51	89.7	9.08	0.1	5,144.25	8.6	964.75	1.6
1999	52,043.18	88.2	8.11	0.0	5,520.49	9.4	1,420.11	2.4
2000	52,855.32	86.1	5.70	0.0	6,306.51	10.3	2,222.15	3.6
2001	31,081.51	84.4	2.94	0.0	3,569.42	9.7	2,168.80	5.9
2002	36,105.22	82.3	429.06	0.9	4,410.90	10.1	2,929.08	6.7
2003	31,885.66	77.8	509.35	1.3	4,714.32	11.5	3,856.24	9.4
2004	36,719.57	75.9	786.44	1.6	5,590.58	11.6	5,258.97	10.9
2005	26,228.77	68.8	918.10	2.4	5,063.87	13.3	5,891.13	15.5
2006	34,118.39	70.6	1,087.56	2.2	5,338.44	11.0	7,809.16	16.2
2007	44,732.66	67.3	1,406.62	2.1	8,648.72	13.0	11,721.40	17.6

Table 2
Summary Statistics

The table reports the summary statistics for the size-institutional ownership and volume-institutional ownership portfolios for the sample period from January 1996 to May 2007. P_{ij} refers to a value-weighted portfolio of size *i* and institutional ownership *j*. *i* = 1, 4 refer to the smallest and largest size portfolios, respectively, and *j* = *l*, *h* refer to the low and high institutional ownership portfolios, respectively. The volume-institutional ownership portfolios are defined analogously. Number of stocks is the average number of stocks in each portfolio. Institutional ownership fraction is the mean monthly institutional ownership fraction of each portfolio. Market capitalization is the mean weekly market capitalization of each portfolio. Turnover is the mean weekly portfolio turnover. The Sharpe ratio is calculated by using the mean monthly portfolio returns over the risk-free rate divided by the portfolio's standard deviation. Abnormal returns are calculated as the intercept from a monthly time series regression of the portfolio excess returns (assuming a holding period of 1, 5, 10, 25, or 140 days) on the market excess returns, a firm-size factor, a value-growth factor, and a momentum factor. The *t*-statistics are reported in parentheses. Detrended log turnover is the mean weekly detrended log portfolio turnover. Return is the mean weekly portfolio return. ADF test for detrended log turnover and that for portfolio return denote the *t*-statistic of the augmented Dickey-Fuller test (1979) for a unit root for portfolio return and detrended portfolio turnover, respectively. ARCH(12) denotes the chi-square statistic of the Lagrange Multiplier (LM) test for autoregressive conditional heteroskedasticity effects with 12 lags.

Panel A: Size-institutional ownership portfolios

P_{ij}	P_{1l}	P_{1h}	P_{2l}	P_{2h}	P_{3l}	P_{3h}	P_{4l}	P_{4h}
Number of stocks	77.2555	77.0000	76.8467	77.0679	76.9562	77.2190	76.7591	77.0803
Institutional ownership fraction (%)	0.2117	8.0964	1.5071	11.4554	6.1896	16.3919	10.7680	25.0309
Market capitalization (NT$ billion)	1.3221	1.5135	3.6004	3.6923	7.9183	8.0537	64.0977	67.3293
Turnover (%)	3.5169	4.0963	4.2308	4.8447	4.7067	5.9437	3.9241	3.6929
Sharpe ratio	0.5817	0.5979	0.4969	0.5159	0.4276	0.4613	0.3883	0.4212
Abnormal returns (1 day, %)	-5.4030**	-4.0290*	-4.2184*	-2.9215*	3.2728	4.3492	5.0335	7.0867*
	(-2.3227)	(-1.7665)	(-1.8239)	(-1.9760)	(0.8832)	(1.2216)	(1.2984)	(1.7280)
Abnormal returns (5 days, %)	-3.7919***	-2.6048**	-2.8363*	-0.2059	-1.8142	-0.2076	3.8106	4.8752***
	(-3.3341)	(-2.5525)	(-1.7844)	(-0.1478)	(-1.2316)	(-0.1577)	(0.5456)	(2.7024)
Abnormal returns (10 days, %)	-1.9900**	-1.9633	-1.6824	-1.8568	3.0173***	4.5197***	2.2853***	2.9851***
	(-2.3593)	(-0.6013)	(-0.8681)	(-1.2654)	(3.2683)	(3.7267)	(2.6467)	(3.6581)
Abnormal returns (25 days, %)	1.9633	1.3202	1.1212*	1.5920***	0.8572*	1.2332	0.9886**	1.4546***
	(0.6013)	(0.9684)	(1.9163)	(2.8689)	(1.7326)	(1.3932)	(2.4548)	(3.5731)
Abnormal returns (140 days, %)	2.5394***	2.0037***	0.9104***	1.8416***	0.7609**	1.0864***	1.0650***	1.2943***
	(5.8898)	(4.8297)	(2.6850)	(5.1966)	(2.2363)	(3.2891)	(3.0473)	(3.5896)
ADF test for detrended log turnover	-24.2648***	-24.3486***	-24.4218***	-24.3821***	-24.3276***	-24.4043***	-24.2830***	-24.4466***

ADF test for return	-11.0670***	-10.8874***	-10.9846***	-11.4078***	-11.3357***	-12.0756***	-12.1265***	-25.5546***
ARCH(12) for return	27.1127***	44.9947***	30.0935***	37.1663***	37.4183***	38.2599***	26.5262***	37.3499***
Panel B: Volume-institutional ownership portfolios								
P_{ij}	P_{1l}	P_{1h}	P_{2l}	P_{2h}	P_{3l}	P_{3h}	P_{4l}	P_{4h}
Number of stocks	76.8759	76.9781	76.8467	77.1459	76.9416	77.2044	76.7518	77.1095
Institutional ownership fraction (%)	1.3806	14.6282	3.4718	17.1024	6.0144	16.9138	6.3961	17.2372
Market capitalization (NT$ billion)	10.0936	29.6293	15.0767	42.0662	12.4177	27.2943	11.7780	21.0434
Turnover (%)	0.9495	1.0280	2.6337	2.7313	4.7104	4.5344	10.5144	10.8134
Sharpe ratio	0.5563	0.5678	0.4187	0.3890	0.3697	0.3861	0.3440	0.4199
Abnormal returns (1 day, %)	-4.2286**	-2.6212***	3.6143	5.2478	6.5678*	8.2327**	7.0868*	9.5404***
	(-2.0441)	(-2.9151)	(1.1310)	(1.3136)	(1.37435)	(2.4340)	(1.7805)	(2.6500)
Abnormal returns (5 days, %)	-3.3298*	-1.3394*	-1.5608	-0.0624	-2.0213	0.0647	5.0159	8.8487**
	(-1.8823)	(1.9236)	(-1.1438)	(-0.0474)	(-1.1871)	(0.0408)	(0.8144)	(2.2449)
Abnormal returns (10 days, %)	-3.2286**	-2.0683	2.9754**	2.0421**	3.6076***	3.4361***	3.2590**	5.3430***
	(-2.0441)	(-1.4532)	(2.5984)	(2.4997)	(3.0098)	(3.7470)	(2.5468)	(3.5417)
Abnormal returns (25 days, %)	1.0159	1.1790**	1.0542	1.8962	1.2114*	1.7513***	0.9384	2.6093***
	(0.8144)	(2.3337)	(1.5106)	(1.3905)	(1.7440)	(3.8707)	(0.4464)	(2.6210)
Abnormal returns (140 days, %)	1.2098***	1.6401***	0.8810***	1.0005***	0.6888*	1.4194***	0.4543	1.3202***
	(3.8261)	(3.7739)	(2.9164)	(2.8103)	(1.7675)	(3.7573)	(1.2510)	(3.1206)
ADF test for detrended log turnover	-24.2222***	-24.2920***	-24.2777***	-24.2761***	-24.2496***	-24.1856***	-24.3996***	-24.3589***
ADF test for return	-10.6460***	-24.4205***	-11.2868***	-26.3935***	-11.7534***	-12.4136***	-11.5562***	-15.8895***
ARCH(12) for return	50.4096***	25.6461**	27.9999***	26.0611**	34.6857***	30.0931***	51.1468***	48.8373***
Panel C: Taiwanese market index								
ADF Test for return	-12.6572***							
ARCH(12) for return	26.4573***							

Notes:
1. Critical values and statistical significance levels for the ADF unit root statistic with more than 500 observations are: -2.5700 at 10%, -2.8600 at 5%, and -3.4300 at 1% (Fuller, 1976, Table 8.5.2, p. 373).
2. ***, **, * denote significant level at the 1%, 5%, and 10%, respectively.

Table 3
Portfolio Turnover Conditional on Past Returns

The table reports the mean weekly portfolio turnover for the size-institutional ownership and volume-institutional ownership portfolios for the sample period from January 1996 to May 2007. $P_{ij\text{-}hm}$ and $P_{ij\text{-}lm}$ refer to a value-weighted portfolio of size *i* and institutional ownership *j* conditional on high and low past positive market returns (i.e., subscript *hm* and *lm*), respectively. *i* = 1, 4 refer to the smallest and largest size portfolios, respectively, and *j* = *l*, *h* refer to the low and high institutional ownership portfolios, respectively. Past positive market returns mean that 3-week buy-and-hold market returns are positive. The volume-institutional ownership portfolios are defined analogously. The t-1($P_{ij\text{-}hm}$=$P_{ij\text{-}lm}$) test statistic is a *t*-statistic that is used to test the null hypothesis that the mean weekly portfolio turnover of $P_{ij\text{-}hm}$ is equal to that of $P_{ij\text{-}lm}$. The t-2($P_{il\text{-}hm}$=$P_{ih\text{-}hm}$) test statistic is a *t*-statistic that is used to test the null hypothesis that the mean weekly portfolio turnover of $P_{il\text{-}hm}$ is equal to that of $P_{ih\text{-}hm}$. The t-3($P_{il\text{-}hm}$=$P_{ih\text{-}lm}$) test statistic is a *t*-statistic that is used to test the null hypothesis that the mean weekly portfolio turnover of $P_{il\text{-}hm}$ is equal to that of $P_{ih\text{-}lm}$. The size-institutional ownership-return portfolios, $P_{ij\text{-}hp}$ and $P_{ij\text{-}lp}$, refer to a value-weighted portfolio of size *i*, institutional ownership *j* and high and low return portfolios, respectively, within each size-institutional ownership group *ij*. The volume-institutional ownership-return portfolios are defined analogously. The t-1($P_{ij\text{-}hp}$=$P_{ij\text{-}lp}$) test statistic is a *t*-statistic that is used to test the null hypothesis that the mean weekly portfolio turnover of $P_{ij\text{-}hp}$ is equal to that of $P_{ij\text{-}lp}$. The t-2($P_{il\text{-}hp}$=$P_{ih\text{-}hp}$) test statistic is a *t*-statistic that is used to test the null hypothesis that the mean weekly portfolio turnover of $P_{il\text{-}hp}$ is equal to that of $P_{ih\text{-}hp}$. The t-3($P_{il\text{-}hp}$=$P_{ih\text{-}lp}$) test statistic is a *t*-statistic that is used to test the null hypothesis that the mean weekly portfolio turnover of $P_{il\text{-}hp}$ is equal to that of $P_{ih\text{-}lp}$.

Panel A: Size-institutional ownership portfolios conditional on past market returns

($P_{ij\text{-}hm}$, $P_{ij\text{-}lm}$)	($P_{1l\text{-}hm}$, $P_{1l\text{-}lm}$)	($P_{1h\text{-}hm}$, $P_{1h\text{-}lm}$)	($P_{2l\text{-}hm}$, $P_{2l\text{-}lm}$)	($P_{2h\text{-}hm}$, $P_{2h\text{-}lm}$)	($P_{3l\text{-}hm}$, $P_{3l\text{-}lm}$)	($P_{3h\text{-}hm}$, $P_{3h\text{-}lm}$)	($P_{4l\text{-}hm}$, $P_{4l\text{-}lm}$)	($P_{4h\text{-}hm}$, $P_{4h\text{-}lm}$)
Turnover (%)	(4.7499, 4.2308)	(3.9428, 3.4603)	(6.4766, 5.6386)	(5.8748, 4.7103)	(7.6296, 6.3202)	(6.1919, 5.1522)	(4.4307, 3.5161)	(4.1998, 3.2264)
t-1($P_{ij\text{-}hm}$=$P_{ij\text{-}lm}$)	1.3131	1.4254	2.0387**	3.1127***	3.9863***	3.1690***	3.3746***	3.6356***
t-2($P_{il\text{-}hm}$=$P_{ih\text{-}hm}$)	5.6293***		3.6713***		7.3953***		2.0053**	
t-3($P_{il\text{-}hm}$=$P_{ih\text{-}lm}$)	3.6156***		4.6598***		8.2466***		4.3603***	

Panel B: Volume-institutional ownership portfolios conditional on past market returns

($P_{ij\text{-}hm}$, $P_{ij\text{-}lm}$)	($P_{1l\text{-}hm}$, $P_{1l\text{-}lm}$)	($P_{1h\text{-}hm}$, $P_{1h\text{-}lm}$)	($P_{2l\text{-}hm}$, $P_{2l\text{-}lm}$)	($P_{2h\text{-}hm}$, $P_{2h\text{-}lm}$)	($P_{3l\text{-}hm}$, $P_{3l\text{-}lm}$)	($P_{3h\text{-}hm}$, $P_{3h\text{-}lm}$)	($P_{4l\text{-}hm}$, $P_{4l\text{-}lm}$)	($P_{4h\text{-}hm}$, $P_{4h\text{-}lm}$)
Turnover (%)	(1.2501, 0.9972)	(1.0426, 0.8759)	(3.3943, 2.7459)	(2.7230, 2.1584)	(6.0384, 5.0724)	(5.3337, 4.4912)	(12.7004, 10.6184)	(11.8501, 10.4626)
t-1($P_{ij\text{-}hm}$=$P_{ij\text{-}lm}$)	2.7099***	1.7928*	2.4336**	3.1179***	2.6403***	2.5024**	3.5617***	2.3237**
t-2($P_{il\text{-}hm}$=$P_{ih\text{-}hm}$)	3.5087***		5.2548***		3.9065***		2.6795***	
t-3($P_{il\text{-}hm}$=$P_{ih\text{-}lm}$)	4.3254***		5.3881***		4.4112***		3.9103****	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Table 4
Bivariate Granger Causality Tests

The following bivariate Seemingly Unrelated Regression (SUR) model is estimated to investigate the causal relation between portfolio volume and market returns for each portfolio over the sample period from January 1996 to May 2007:

$$V_{ij,t} = \alpha_{ij,1} + \sum_{a=0}^{A} \beta_{ij,11a} DAVR_{m,t-a} + \sum_{b=0}^{B} \beta_{ij,12b} DMAD_{ij,t-b} + \sum_{c=1}^{C} \beta_{ij,13c} R_{ij,t-c} + \sum_{d=1}^{D} \gamma_{ij,11d} V_{ij,t-d} + \sum_{d=1}^{D} \gamma_{ij,12d} R_{m,t-d} + \varepsilon_{ij,1t}, \quad (5)$$

$$R_{m,t} = \alpha_{ij,2} + \sum_{d=1}^{D} \gamma_{ij,21d} V_{ij,t-d} + \sum_{d=1}^{D} \gamma_{ij,22d} R_{m,t-d} + \varepsilon_{ij,2t}, \quad (6)$$

where $V_{ij,t}$ is the value-weighted detrended trading volume of portfolio ij, $R_{m,t}$ is the return on a value-weighted Taiwanese market index, $R_{ij,t}$ is the return of portfolio ij, $DAVR_{m,t}$ is the detrended absolute value of $R_{m,t}$ and $DMAD_{ij,t}$ is the detrended value-weighted average of the beta-adjusted differences between the returns of stocks in portfolio ij and the return on a value-weighted Taiwanese market index. P_{ij} refers to a value-weighted portfolio of size i and institutional ownership j. i = 1, 4 refer to the smallest and largest size portfolios, respectively, and $j = l$, h refer to the low and high institutional ownership portfolios, respectively. The volume-institutional ownership portfolios are defined analogously. The number of lags in each equation is chosen by considering both the Akaike (1974) information criterion (AIC) and the Schwarz (1978) information criterion (SIC). The *W-D* statistic is the chi-square statistic with D degrees of freedom obtained from a joint test of the null hypothesis based on the causality restrictions. The *W*-1 statistic is the chi-square statistic with one degree of freedom under the null hypothesis that the sum of the lagged coefficients is equal to zero. The *W-D* and *W*-1 statistics are reported in parentheses.

Panel A: Size-institutional ownership portfolios

P_{ij}	Hypothesis 1	Does causality exist? (*W-D* statistic)	Sum of lagged coefficients	Hypothesis 2	Sign of causality (*W*-1 statistic)
P_{1l}	$\gamma_{1l,12d} = 0$ for all d	Yes (19.4919***)	$\sum_{d=1}^{2} \gamma_{1l,12d} = 0.0382$	$\sum_{d=1}^{2} \gamma_{1l,12d} = 0$	Positive (19.4514***)
	$\gamma_{1l,21d} = 0$ for all d	No (0.1566)	$\sum_{d=1}^{2} \gamma_{1l,21d} = 0.0466$		
P_{1h}	$\gamma_{1h,12d} = 0$ for all d	Yes (21.2543***)	$\sum_{d=1}^{2} \gamma_{1h,12d} = 0.0285$	$\sum_{d=1}^{2} \gamma_{1h,12d} = 0$	Positive (21.1123***)
	$\gamma_{1h,21d} = 0$ for all d	No (0.0658)	$\sum_{d=1}^{2} \gamma_{1h,21d} = 0.0559$		
P_{2l}	$\gamma_{2l,12d} = 0$ for all d	Yes (15.8748***)	$\sum_{d=1}^{2} \gamma_{2l,12d} = 0.0446$	$\sum_{d=1}^{2} \gamma_{2l,12d} = 0$	Positive (15.7221***)
	$\gamma_{2l,21d} = 0$ for all d	No (0.7614)	$\sum_{d=1}^{2} \gamma_{2l,21d} = -0.1864$		
P_{2h}	$\gamma_{2h,12d} = 0$ for all d	Yes (11.2518***)	$\sum_{d=1}^{2} \gamma_{2h,12d} = 0.0150$	$\sum_{d=1}^{2} \gamma_{2h,12d} = 0$	Positive (11.1957***)
	$\gamma_{2h,21d} = 0$ for all d	No (1.9206)	$\sum_{d=1}^{2} \gamma_{2h,21d} = 0.2649$		
P_{3l}	$\gamma_{3l,12d} = 0$ for all d	Yes (39.4826***)	$\sum_{d=1}^{3} \gamma_{3l,12d} = 0.0569$	$\sum_{d=1}^{3} \gamma_{3l,12d} = 0$	Positive (35.7789***)

	$\gamma_{3l,21d} = 0$ for all d	No (0.1821)	$\sum_{d=1}^{3}\gamma_{3l,21d} = -0.0394$		
P_{3h}	$\gamma_{3h,12d} = 0$ for all d	Yes (20.0066***)	$\sum_{d=1}^{3}\gamma_{3h,12d} = 0.0386$	$\sum_{d=1}^{3}\gamma_{3h,12d} = 0$	Positive (19.5085***)
	$\gamma_{3h,21d} = 0$ for all d	No (0.7447)	$\sum_{d=1}^{3}\gamma_{3h,21d} = 0.0237$		
P_{4l}	$\gamma_{4l,12d} = 0$ for all d	Yes (18.6134***)	$\sum_{d=1}^{2}\gamma_{4l,12d} = 0.0270$	$\sum_{d=1}^{2}\gamma_{4l,12d} = 0$	Positive (18.5008***)
	$\gamma_{4l,21d} = 0$ for all d	No (0.6602)	$\sum_{d=1}^{2}\gamma_{4l,21d} = 0.0926$		
P_{4h}	$\gamma_{4h,12d} = 0$ for all d	Yes (8.9104**)	$\sum_{d=1}^{2}\gamma_{4h,12d} = 0.0165$	$\sum_{d=1}^{2}\gamma_{4h,12d} = 0$	Positive (8.6879***)
	$\gamma_{4h,21d} = 0$ for all d	No (2.2133)	$\sum_{d=1}^{2}\gamma_{4h,21d} = 0.8744$		

Panel B: Volume-institutional ownership portfolios

P_{ij}	Hypothesis 1	Does causality exist? (*W-D* statistic)	Sum of lagged coefficients	Hypothesis 2	Sign of causality (*W*-1 statistic)
P_{1l}	$\gamma_{1l,12d} = 0$ for all d	Yes (15.2076***)	$\sum_{d=1}^{2}\gamma_{1l,12d} = 0.0420$	$\sum_{d=1}^{2}\gamma_{1l,12d} = 0$	Positive (14.7837***)
	$\gamma_{1l,21d} = 0$ for all d	No (1.7239)	$\sum_{d=1}^{2}\gamma_{1l,21d} = -0.3263$		
	$\gamma_{1h,12d} = 0$ for all d	Yes (14.0081***)	$\sum_{d=1}^{2}\gamma_{1h,12d} = 0.0233$	$\sum_{d=1}^{2}\gamma_{1h,12d} = 0$	Positive (13.8664***)
P_{1h}	$\gamma_{1h,21d} = 0$ for all d	No (2.9002)	$\sum_{d=1}^{2}\gamma_{1h,21d} = 0.5431$		
P_{2l}	$\gamma_{2l,12d} = 0$ for all d	Yes (16.3175***)	$\sum_{d=1}^{2}\gamma_{2l,12d} = 0.0291$	$\sum_{d=1}^{2}\gamma_{2l,12d} = 0$	Positive (15.2397***)
	$\gamma_{2l,21d} = 0$ for all d	No (1.3756)	$\sum_{d=1}^{2}\gamma_{2l,21d} = -0.3052$		
P_{2h}	$\gamma_{2h,12d} = 0$ for all d	Yes (11.2518***)	$\sum_{d=1}^{2}\gamma_{2h,12d} = 0.0150$	$\sum_{d=1}^{2}\gamma_{2h,12d} = 0$	Positive (11.1957***)
	$\gamma_{2h,21d} = 0$ for all d	No (1.9206)	$\sum_{d=1}^{2}\gamma_{2h,21d} = 0.2649$		
P_{3l}	$\gamma_{3l,12d} = 0$ for all d	Yes (33.6285***)	$\sum_{d=1}^{3}\gamma_{3l,12d} = 0.0479$	$\sum_{d=1}^{3}\gamma_{3l,12d} = 0$	Positive (31.6329***)
	$\gamma_{3l,21d} = 0$ for all d	No (1.3481)	$\sum_{d=1}^{3}\gamma_{3l,21d} = 0.2383$		
P_{3h}	$\gamma_{3h,12d} = 0$ for all d	Yes (14.3001***)	$\sum_{d=1}^{3}\gamma_{3h,12d} = 0.0258$	$\sum_{d=1}^{3}\gamma_{3h,12d} = 0$	Positive (12.9505***)
	$\gamma_{3h,21d} = 0$ for all d	No (2.9597)	$\sum_{d=1}^{3}\gamma_{3h,21d} = -0.0518$		
P_{4l}	$\gamma_{4l,12d} = 0$ for all d	Yes (34.4449***)	$\sum_{d=1}^{3}\gamma_{4l,12d} = 0.0452$	$\sum_{d=1}^{3}\gamma_{4l,12d} = 0$	Positive (31.9604***)
	$\gamma_{4l,21d} = 0$ for all d	No (0.1311)	$\sum_{d=1}^{3}\gamma_{4l,21d} = -0.1370$		
P_{4h}	$\gamma_{4h,12d} = 0$ for all d	Yes (6.4455*)	$\sum_{d=1}^{3}\gamma_{4h,12d} = 0.0176$	$\sum_{d=1}^{3}\gamma_{4h,12d} = 0$	Positive (5.6475**)
	$\gamma_{4h,21d} = 0$ for all d	No (5.6475**)	$\sum_{d=1}^{3}\gamma_{4h,21d} = 0.3861$		

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Table 5
Causal Relation across Portfolios

The following bivariate Seemingly Unrelated Regression (SUR) model is estimated to investigate the causal relation between portfolio volume and market returns across the low and high institutional ownership portfolios within each size and volume quartile over the sample period from January 1996 to May 2007:

$$V_{ij,t} = \alpha_{ij} + \beta_{ij1} DAVR_{m,t} + \beta_{ij2} DMAD_{ij,t} + \sum_{k=1}^{K} \gamma_{ijk} R_{m,t-k} + \varepsilon_{ij,t}, \quad \text{for } j = l \text{ and } h, \text{ given } i = 1,\ldots, 4, \tag{7}$$

where $V_{ij,t}$ is the value-weighted detrended trading volume of portfolio *ij*, $R_{m,t}$ is the return on a value-weighted Taiwanese market index, $DAVR_{m,t}$ is the detrended absolute value of $R_{m,t}$ and $DMAD_{ij,t}$ is the detrended value-weighted average of the beta-adjusted differences between the returns of stocks in portfolio *ij* and the return on a value-weighted Taiwanese market index. P_{ij} refers to a value-weighted portfolio of size *i* and institutional ownership *j*. *i* = 1, 4 refer to the smallest and largest size portfolios, respectively, and *j* = *l*, *h* refer to the low and high institutional ownership portfolios, respectively. The volume-institutional ownership portfolios are defined analogously. The W-$K(\gamma)$ test statistic follows a chi-square distribution with *K* degrees of freedom under the null hypothesis that $\gamma_{ijk} = 0$, for all *k*. The W-$1(\gamma)$ test statistics follows a chi-square distribution with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ijk} = 0$. The W-$1(\gamma_{il}=\gamma_{ih})$ test statistic follows a chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ilk} = \sum_k \gamma_{ihk}$. $\overline{R}^2$ is the adjusted coefficient of determination. $Q(12)$ is the Ljung-Box Q-statistic used to test the joint significance of the autocorrelation up to 12 lags for the residuals in each regression. The *p*-values are reported in brackets beneath the test statistics.

Panel A: Size-institutional ownership portfolios

P_{il} vs. P_{ih}	P_{1l} vs. P_{1h}		P_{2l} vs. P_{2h}		P_{3l} vs. P_{3h}		P_{4l} vs. P_{4h}	
Dependent variable	$V_{1l,t}$	$V_{1h,t}$	$V_{2l,t}$	$V_{2h,t}$	$V_{3l,t}$	$V_{3h,t}$	$V_{4l,t}$	$V_{4h,t}$
Lag Length	2	2	2	2	3	3	2	2
W-$K(\gamma)$	34.7538***	27.7211***	18.5454***	16.2424***	48.1831***	27.6394***	20.2468***	8.4529**
$\sum_k \gamma_{ijk}$	0.0490	0.0313	0.0447	0.0230	0.0556	0.0400	0.0249	0.0149
W-$1(\gamma)$	34.7383***	27.6295***	18.3037***	16.0131***	44.1570***	27.0989***	19.6947***	7.9265***
Do investors trade overconfidently?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
W-$1(\gamma_{il}=\gamma_{ih})$	15.6096***		7.2354***		5.4767**		7.1466***	
Do individual investors trade more overconfidently than institutional investors?	Yes		Yes		Yes		Yes	
$\overline{R}^2$	0.2462	0.1545	0.1811	0.2171	0.2416	0.2091	0.2523	0.2186
$Q(12)$	5.5352	8.4416	4.1323	6.0625	4.6436	8.5629	14.6023	12.7657

Panel B: Volume-institutional ownership portfolios

P_{il} vs. P_{ih}	P_{1l} vs. P_{1h}		P_{2l} vs. P_{2h}		P_{3l} vs. P_{3h}		P_{4l} vs. P_{4h}	
Dependent variable	$V_{1l,t}$	$V_{1h,t}$	$V_{2l,t}$	$V_{2h,t}$	$V_{3l,t}$	$V_{3h,t}$	$V_{4l,t}$	$V_{4h,t}$
Lag Length	2	2	2	2	3	3	3	3
$W\text{-}K(\gamma)$	15.9248***	14.9392***	19.4521***	11.0707***	34.3996***	12.8443***	26.5099***	7.7262*
$\sum_k \gamma_{ijk}$	0.0420	0.0230	0.0302	0.0142	0.0431	0.0230	0.0363	0.0188
$W\text{-}1(\gamma)$	15.4173***	14.6576***	18.2309***	11.0588***	31.7993***	11.4731***	25.3486***	7.4171***
Do investors trade overconfidently?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$W\text{-}1(\gamma_l = \gamma_h)$	4.6659**		7.6575***		11.3149***		8.4940***	
Do individual investors trade more overconfidently than institutional investors?	Yes		Yes		Yes		Yes	
$\overline{R}^2$	0.0423	0.2104	0.2779	0.2456	0.2071	0.2181	0.1414	0.1528
$Q(12)$	6.4983	8.1150	11.2867	11.8460	12.7558	10.8780	9.8381	4.7357

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Table 6
Causal Relation across Portfolios: Conditional on the Market States

The following bivariate Seemingly Unrelated Regression (SUR) model is estimated to investigate the causal relation between portfolio volume and market returns conditional on the market states across the low and high institutional ownership portfolios within each size quartile over the sample period from January 1996 to May 2007:

$$\begin{aligned} V_{ij,t} &= \alpha_{ij} + \beta_{ij1} DAVR_{m,t} \times D_t + \beta_{ij2} DAVR_{m,t} \times (1-D_t) + \beta_{ij3} DMAD_{i,t} \times D_t \\ &+ \beta_{ij4} DMAD_{i,t} \times (1-D_t) + \sum_{k=1}^{K} \gamma_{ij1k} R_{m,t-k} \times D_{t-k} + \sum_{k=1}^{K} \gamma_{ij2k} R_{m,t-k} \times (1-D_{t-k}) + \varepsilon_{ij,t}, \end{aligned} \quad \text{for } j = l \text{ and } h, \text{ given } i = 1,\ldots,4, \tag{8}$$

where $V_{ij,t}$ is the value-weighted detrended trading volume of portfolio ij, $R_{m,t}$ is the return on a value-weighted Taiwanese market index, $DAVR_{m,t}$ is the detrended absolute value of $R_{m,t}$ and $DMAD_{ij,t}$ is the detrended value-weighted average of the beta-adjusted differences between the returns of stocks in portfolio ij and the return on a value-weighted Taiwanese market index. The dummy variable D_t represents $BU_{g,t}$ and takes on a value of one if week t is included in the period from g weeks after the beginning of CEPD-dated expansion to the end of CEPD-dated expansion, and zero otherwise. Alternatively, the dummy variable D_t represents $WRSS_t$ and takes on a value of one if the momentum indicator $WRSS_t$ constructed from the weighted relative strength strategy is non-negative, and zero otherwise. P_{ij} refers to a value-weighted portfolio of size i and institutional ownership j. i = 1, 4 refer to the smallest and largest size portfolios, respectively, and $j = l$, h refer to the low and high institutional ownership portfolios, respectively. The $W\text{-}K(\gamma_1)$ and $W\text{-}K(\gamma_2)$ statistics are the chi-square statistics with K degrees of freedom under the null hypothesis that $\gamma_{ij1k} = 0$, for all k and that $\gamma_{ij2k} = 0$, for all k, respectively. The $W\text{-}1(\gamma_1)$ and $W\text{-}1(\gamma_2)$ statistics are the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ij1k} = 0$ and $\sum_k \gamma_{ij2k} = 0$, respectively. The $W\text{-}1(\gamma_1{=}\gamma_2)$ statistic is the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ij1k} = \sum_k \gamma_{ij2k}$. The $W\text{-}1(\gamma_{l1}{=}\gamma_{h1})$ statistic is the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{il1k} = \sum_k \gamma_{ih1k}$. $\bar{R}^2$ is the adjusted coefficient of determination. $Q(12)$ is the Ljung-Box Q-statistic used to test the joint significance of the autocorrelation up to 12 lags for the residuals in each regression. The p-values are reported in brackets beneath the test statistics.

Panel A: The dummy variable D_t is $BU_{2,t}$

P_{il} vs. P_{ih}	P_{1l} vs. P_{1h}		P_{2l} vs. P_{2h}		P_{3l} vs. P_{3h}		P_{4l} vs. P_{4h}	
Dependent variable	$V_{1l,t}$	$V_{1h,t}$	$V_{2l,t}$	$V_{2h,t}$	$V_{3l,t}$	$V_{3h,t}$	$V_{4l,t}$	$V_{4h,t}$
Lag Length	2	2	2	2	3	3	2	2
$W\text{-}K(\gamma_1)$	25.4346***	25.3059***	20.4782***	18.3184***	39.5040***	18.0207***	14.9874***	7.8784**
$\sum_k \gamma_{ij1k}$	0.0673	0.0455	0.0734	0.0351	0.0763	0.0486	0.0332	0.0212
$W\text{-}1(\gamma_1)$	25.4001***	25.2765***	20.4287***	16.2458***	35.9632***	17.1191***	13.9395***	6.9517***
Do investors trade overconfidently in bull markets?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$W\text{-}K(\gamma_2)$	12.0039***	6.9979**	2.8222	4.2500	14.9676***	12.7099***	7.2179**	1.9934
$\sum_k \gamma_{ij2k}$	0.0343	0.0208	0.0203	0.0152	0.0412	0.0355	0.0186	0.0099

W-1(γ_2)	11.9667***	6.9514***	2.0651	4.0140**	13.8406***	12.0423***	7.2135***	1.9933
Do investors trade overconfidently in non-bull markets?	Yes	Yes	No	No	Yes	Yes	Yes	No
W-1(γ_1=γ_2)	3.9266**	4.2015**	6.0579**	2.9601*	4.3311**	0.7117	1.6597	1.1269
Do investors trade more overconfidently in bull markets than in non-bull markets?	Yes	Yes	Yes	Yes	Yes	No	No	No
W-1(γ_{l1}=γ_{h1})	8.8442***		9.1712***		7.5651***		4.1249**	
Do individual investors trade more overconfidently in bull markets than institutional investors?	Yes		Yes		Yes		Yes	
$\overline{R}^2$	0.2441	0.1556	0.1574	0.2249	0.2437	0.2057	0.2515	0.2200
Q(12)	6.0427	9.4370	5.0930	7.0516	6.3149	9.5950	15.2292	12.8622

Panel B: The dummy variable D_t is $WRSS_t$

P_{il} vs. P_{ih}	P_{1l} vs. P_{1h}		P_{2l} vs. P_{2h}		P_{3l} vs. P_{3h}		P_{4l} vs. P_{4h}	
Dependent variable	$V_{1l,t}$	$V_{1h,t}$	$V_{2l,t}$	$V_{2h,t}$	$V_{3l,t}$	$V_{3h,t}$	$V_{4l,t}$	$V_{4h,t}$
Lag Length	2	2	2	2	3	3	2	2
W-K(γ_1)	32.8767***	26.6409***	10.7677***	9.2227***	38.6117***	18.5700***	21.3864***	7.7275**
$\sum_k \gamma_{ij1k}$	0.0663	0.0429	0.0471	0.0238	0.0686	0.0441	0.0353	0.0186
W-1(γ_1)	31.7572***	26.0710***	10.0470***	8.8375***	35.4872***	17.4645***	19.8910***	6.1458**
Do investors trade overconfidently in up-momentum states?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
W-K(γ_2)	11.6404***	8.7453**	11.9911***	9.5488***	18.5185***	15.4903***	11.2081***	9.0190**
$\sum_k \gamma_{ij2k}$	0.0332	0.0199	0.0392	0.0182	0.0376	0.0348	0.0168	0.0132
W-1(γ_2)	9.1197***	6.4405**	9.6349***	7.0712***	11.7003***	11.8616***	5.4589**	3.7938*
Do investors trade overconfidently in down-momentum states?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
W-1(γ_1=γ_2)	4.3641**	4.1119**	0.1684	0.2875	3.8663**	0.4171	3.0873*	0.2854
Do investors trade more overconfidently in up-momentum	Yes	Yes	No	No	Yes	No	Yes	No

states than in down-momentum states?								
W-1($\gamma_{il1}=\gamma_{ih1}$)	13.7850***		4.0835**		7.2623***		10.0867***	
Do individual investors trade more overconfidently in up-momentum states than institutional investors?	Yes		Yes		Yes		Yes	
$\overline{R}^2$	0.2480	0.1614	0.1794	0.2366	0.2436	0.2095	0.2564	0.2196
$Q(12)$	5.2999	7.4751	3.7287	6.3395	4.8995	8.1003	13.7186	12.0315

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Table 7
Causal Relation across Portfolios: Conditional on Market Volatility

The following bivariate Seemingly Unrelated Regression (SUR) model is estimated to investigate the causal relation between portfolio volume and market returns conditional on market volatility across the low and high institutional ownership portfolios within each size and volume quartile over the sample period from January 1996 to May 2007:

$$V_{ij,t} = \alpha_{ij} + \beta_{ij1} DAVR_{m,t} + \beta_{ij2} DAVR_{m,t} \times HV_t + \beta_{ij3} DAVR_{m,t} \times LV_t + \beta_{ij4} DMAD_{i,t} + \beta_{ij5} DMAD_{i,t} \times HV_t + \beta_{ij6} DMAD_{i,t} \times LV_t$$
$$+ \sum_{k=1}^{K} \gamma_{ij1k} R_{m,t-k} + \sum_{k=1}^{K} \gamma_{ij2k} R_{m,t-k} \times HV_{t-k} + \sum_{k=1}^{K} \gamma_{ij3k} R_{m,t-k} \times LV_{t-k} + \varepsilon_{ij,t}, \quad \text{for } j = l \text{ and } h, \text{ given } i = 1,\ldots, 4, \qquad (9)$$

where $V_{ij,t}$ is the value-weighted detrended trading volume of portfolio *ij*, $R_{m,t}$ is the return on a value-weighted Taiwanese market index, $DAVR_{m,t}$ is the detrended absolute value of $R_{m,t}$ and $DMAD_{ij,t}$ is the detrended value-weighted average of the beta-adjusted differences between the returns of stocks in portfolio *ij* and the return on a value-weighted Taiwanese market index. The dummy variable HV_t (LV_t) takes on a value of one if the conditional market volatility falls in the top (bottom) 30% of its distribution. P_{ij} refers to a value-weighted portfolio of size *i* and institutional ownership *j*. *i* = 1, 4 refer to the smallest and largest size portfolios, respectively, and *j* = *l*, *h* refer to the low and high institutional ownership portfolios, respectively. The volume-institutional ownership portfolios are defined analogously. The W-$K(\gamma_1)$, W-$K(\gamma_2)$, and W-$K(\gamma_3)$ statistics are the chi-square statistics with *K* degrees of freedom under the null hypothesis that $\gamma_{ij1k} = 0$, for all *k*, that $\gamma_{ij2k} = 0$, for all *k*, and that $\gamma_{ij3k} = 0$, for all *k*, respectively. The W-$1(\gamma_1)$, W-$1(\gamma_2)$, and W-$1(\gamma_3)$ statistics are the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ij1k} = 0$, that $\sum_k \gamma_{ij2k} = 0$, and that $\sum_k \gamma_{ij3k} = 0$, respectively. The W-$1(\gamma_1+\gamma_2=\gamma_1+\gamma_3)$ statistic is the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{il1k} + \sum_k \gamma_{il2k} = \sum_k \gamma_{ih1k} + \sum_k \gamma_{ih2k}$. The W-$1(\gamma_{l2}=\gamma_{h2})$ statistic is the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{il2k} = \sum_k \gamma_{ih2k}$. $\bar{R}^2$ is the adjusted coefficient of determination. $Q(12)$ is the Ljung-Box Q-statistic used to test the joint significance of the autocorrelation up to 12 lags for the residuals in each regression. The *p*-values are reported in brackets beneath the test statistics.

Panel A: Size-institutional ownership portfolios

P_{il} vs. P_{ih}	P_{1l} vs. P_{1h}		P_{2l} vs. P_{2h}		P_{3l} vs. P_{3h}		P_{4l} vs. P_{4h}	
Dependent variable	$V_{1l,t}$	$V_{1h,t}$	$V_{2l,t}$	$V_{2h,t}$	$V_{3l,t}$	$V_{3h,t}$	$V_{4l,t}$	$V_{4h,t}$
Lag length	2	2	2	2	3	3	2	2
W-$K(\gamma_1)$	7.5033**	6.4728**	6.3199**	5.8684*	13.8657***	4.1080	3.9412	1.6612
$\sum_k \gamma_{ij1k}$	0.0344	0.0230	0.0371	0.0197	0.0422	0.0231	0.0164	0.0097
W-$1(\gamma_1)$	7.4391***	6.4568**	5.3938**	5.1169**	11.4643***	4.0364**	3.7008*	1.4671
Do investors trade overconfidently in medium-volatility market states?	Yes	Yes	Yes	Yes	Yes	No	No	No
W-$K(\gamma_2)$	0.6751	0.1417	0.5183	0.6324	1.1252	1.9798	0.0509	0.0887
$\sum_k \gamma_{ij2k}$	0.0135	0.0044	-0.0033	-0.0016	0.0105	0.0219	0.0017	-0.0025
W-$1(\gamma_2)$	0.6442	0.1341	0.0242	0.0190	0.3811	1.9600	0.0236	0.0551
Do investors trade more overconfidently in high-volatility	No	No	No	No	No	No	No	No

market states than in medium-volatility market states?								
W-$K(\gamma_3)$	6.4236**	6.7707**	4.9931*	3.2886	9.8584**	10.7370**	12.9929**	8.7120**
$\sum_k \gamma_{ij3k}$	0.0679	0.0502	0.0744	0.0340	0.0686	0.0538	0.0655	0.0497
W-1(γ_3)	6.3204**	6.7595***	4.7231**	3.2743*	6.8340***	5.0431**	12.9236***	8.3375***
Do investors trade more overconfidently in low-volatility market states than in medium-volatility market states?	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
W-1$(\gamma_1+\gamma_2=\gamma_1+\gamma_3)$	9.4297***	11.0681***	9.7998***	7.5154***	12.5778***	4.5066**	16.9018***	11.3731***
Do investors trade more overconfidently in low-volatility market states than in high-volatility market states?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
W-1$(\gamma_{l2}=\gamma_{h2})$	11.5411***		1.8755		0.6336		4.1201**	
Do individual investors trade more overconfidently in high-volatility market states than institutional investors?	Yes		No		No		Yes	
$\overline{R}^2$	0.2483	0.1581	0.1819	0.2207	0.2453	0.2116	0.2593	0.2242
$Q(12)$	5.7913	9.2127	4.1149	7.5150	6.5402	9.6250	15.6666	12.9175

Panel B: Volume-institutional ownership portfolios

P_{il} vs. P_{ih}	P_{1l} vs. P_{1h}		P_{2l} vs. P_{2h}		P_{3l} vs. P_{3h}		P_{4l} vs. P_{4h}	
Dependent variable	$V_{1l,t}$	$V_{1h,t}$	$V_{2l,t}$	$V_{2h,t}$	$V_{3l,t}$	$V_{3h,t}$	$V_{4l,t}$	$V_{4h,t}$
Lag length	2	2	2	2	3	3	3	3
W-$K(\gamma_1)$	5.5393*	3.7444	6.3997**	3.8507	6.9866*	3.5745	8.2035**	1.4168
$\sum_k \gamma_{ij1k}$	0.0348	0.0145	0.0243	0.0119	0.0279	0.0143	0.0301	0.0084
W-1(γ_1)	4.6026**	2.5209	5.0982**	3.4251*	5.9761**	1.9912	7.8117***	0.6525
Do investors trade overconfidently in medium-volatility market states?	Yes	No	Yes	No	Yes	No	Yes	No
W-$K(\gamma_2)$	0.5127	1.7321	0.4542	1.9686	1.5549	1.5376	0.1307	1.2929
$\sum_k \gamma_{ij2k}$	-0.0075	0.0025	-0.0010	-0.0089	0.0157	0.0035	0.0003	0.0131
W-1(γ_2)	0.1181	0.0418	0.0058	1.0871	1.0157	0.0625	0.0006	0.8577
Do investors trade more overconfidently in high-volatility market states than in medium-volatility market states?	No	No	No	No	No	No	No	No
W-$K(\gamma_3)$	7.1418**	10.0631***	6.0210**	16.2929***	12.6515***	10.6044**	11.0341**	6.9216*

$\sum_k \gamma_{ij3k}$	0.0928	0.0598	0.0569	0.0544	0.0607	0.0563	0.0486	0.0432
W-1(γ_3)	7.1109***	9.4358***	6.0204**	15.7018***	6.5703**	7.0442***	4.7129**	3.9392**
Do investors trade more overconfidently in low-volatility market states than in medium-volatility market states?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
W-1($\gamma_1+\gamma_2=\gamma_1+\gamma_3$)	13.1742***	9.4358***	11.0169***	26.3239***	8.0986***	8.6436***	10.5185***	2.6813
Do investors trade more overconfidently in low-volatility market states than in high-volatility market states?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
W-1($\gamma_{l2}=\gamma_{h2}$)	0.6920		6.1329**		8.7557***		1.0433	
Do individual investors trade more overconfidently in high-volatility market states than institutional investors?	No		Yes		Yes		No	
$\bar{R}^2$	0.0569	0.2201	0.2783	0.2710	0.2173	0.2245	0.1480	0.1500
$Q(12)$	7.8113	7.6850	12.5722	12.9603	15.9403	12.3035	10.1605	4.9873

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Table 8
Causal Relation across Portfolios: Conditional on the Risk Level of Stocks

The following multivariate Seemingly Unrelated Regression (SUR) model is estimated to investigate the causal relation between portfolio volume and market returns conditional on the risk level of stocks across the four institutional ownership-risk portfolios within each size quartile over the sample period from January 1996 to May 2007:

$$V_{ijs,t} = \alpha_{ijs} + \beta_{ijs1} DAVR_{m,t} + \beta_{ijs2} DMAD_{ijs,t} + \sum_{k=1}^{K} \gamma_{ijsk} R_{m,t-k} + \varepsilon_{ijs,t}, \quad \text{for } j, s = l \text{ and } h, \text{ given } i = 1,\ldots, 4, \tag{11}$$

where $V_{ijs,t}$ is the value-weighted detrended trading volume of portfolio *ijs*, $R_{m,t}$ is the return on a value-weighted Taiwanese market index, $DAVR_{m,t}$ is the detrended absolute value of $R_{m,t}$, and $DMAD_{ijs,t}$ is detrended the value-weighted average of the beta-adjusted differences between the returns of stocks in portfolio *ijs* and the return on a value-weighted Taiwanese market index. P_{ijs} refers to a value-weighted portfolio of size *i*, institutional ownership *j*, and firm-specific risk level *s*. *i* = 1, 4 refer to the smallest and largest size portfolios, respectively, *j* = *l*, *h* refer to the low and high institutional ownership portfolios, respectively, and *s* = *l*, *h* refer to the lowest and highest firm-specific risk portfolios, respectively, within each size-institutional ownership group *ij*. The $W\text{-}K(\gamma_{ijs})$ statistic is the chi-square statistics with *K* degrees of freedom under the null hypothesis that $\gamma_{ijsk} = 0$, for all *k*. The $W\text{-}1(\gamma_{ijs})$ statistic is the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ijsk} = 0$. The $W\text{-}1(\gamma_{ijl}=\gamma_{ijh})$ statistic is the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ijlk} = \sum_k \gamma_{ijhk}$. The $W\text{-}1(\gamma_{ilh}=\gamma_{ihh})$ statistic is the chi-square statistic with one degree of freedom under the null hypothesis that $\sum_k \gamma_{ilhk} = \sum_k \gamma_{ihhk}$. $\bar{R}^2$ is the adjusted coefficient of determination. *Q*(12) is the Ljung-Box *Q*-statistic used to test the joint significance of the autocorrelation up to 12 lags for the residuals in each regression. The *p*-values are reported in brackets beneath the test statistics.

Size *i*	Size 1				Size 2			
P_{ijs}	P_{1ll}	P_{1lh}	P_{1hl}	P_{1hh}	P_{2ll}	P_{2lh}	P_{2hl}	P_{2hh}
Dependent variable	$V_{1ll,t}$	$V_{1lh,t}$	$V_{1hl,t}$	$V_{1hh,t}$	$V_{2ll,t}$	$V_{2lh,t}$	$V_{2hl,t}$	$V_{2hh,t}$
Lag length	2	2	2	2	2	2	2	2
$W\text{-}K(\gamma_{ijs})$	12.1698***	27.3546***	5.5364*	14.1895***	16.0326***	16.5984***	16.9097***	20.3233***
$\sum_k \gamma_{ijsk}$	0.0242	0.0516	0.0184	0.0282	0.0255	0.0514	0.0238	0.0306
$W\text{-}1(\gamma_{ijs})$	12.0982***	26.5428***	5.5364**	10.4357***	15.9821***	16.5639***	15.3960***	19.0766***
Do investors trade overconfidently in less or more risky securities?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$W\text{-}1(\gamma_{ijl}=\gamma_{ijh})$	8.2700***		1.2865		4.9344**		1.1338	
Do investors trade more overconfidently in riskier securities than in less risky securities?	Yes		No		Yes		No	

W-1(γ_{ilh}=γ_{ihh})		5.1632**				3.2330*		
Do individual investors trade more overconfidently in riskier securities than institutional investors?		Yes				Yes		
$\overline{R}^2$	0.1973	0.1908	0.1487	0.1717	0.1646	0.1226	0.2206	0.1707
Q(12)	8.6935	3.9420	11.6592	6.3100	5.7473	9.2610	10.5735	8.4330
Size i		Size 3				Size 4		
P_{ijs}	P_{3ll}	P_{3lh}	P_{3hl}	P_{3hh}	P_{4ll}	P_{4lh}	P_{4hl}	P_{4hh}
Dependent variable	$V_{3ll,t}$	$V_{3lh,t}$	$V_{3hl,t}$	$V_{3hh,t}$	$V_{4ll,t}$	$V_{4lh,t}$	$V_{4hl,t}$	$V_{4hh,t}$
Lag length	3	3	3	3	2	2	2	2
W-K(γ_{ijs})	16.3448***	28.6143***	25.1041***	18.5535***	2.4403	19.1096***	5.0994*	3.5336
$\sum_k \gamma_{ijsk}$	0.0276	0.0643	0.0369	0.0336	0.0102	0.0310	0.0118	0.0117
W-1(γ_{ijs})	10.4012***	25.0627***	24.0426****	16.8652***	2.4366	18.7467***	3.5336	3.4962*
Do investors trade overconfidently in less or more risky securities?	Yes	Yes	Yes	Yes	No	Yes	No	No
W-1(γ_{ijl}=γ_{ijh})	9.3117***		0.1697		9.0971***		0.0003	
Do investors trade more overconfidently in riskier securities than in less risky securities?	Yes		No		Yes		No	
W-1(γ_{ilh}=γ_{ihh})		7.2696***				8.3015***		
Do individual investors trade more overconfidently in riskier securities than institutional investors?		Yes				Yes		
$\overline{R}^2$	0.2248	0.1253	0.1683	0.1689	0.1987	0.1720	0.1964	0.1700
Q(12)	5.8661	8.3125	6.1002	6.0399	7.8458	11.4971	9.7191	9.9027

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.