Overconfidence, trading volume and the disposition effect: Evidence from the Shenzhen Stock Market of China

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It has been a challenge for financial economists to explain some stylized facts observed on securities markets, among them, high levels of trading volume. The most prominent explanation of excess volume is overconfidence. High market returns make investors overconfident and as a consequence, these investors trade more subsequently. Otherwise, excess volume can also be explained by disposition effect describing the tendency to sell stocks that have appreciated in price, but not those that have depreciated in price. The aim of our paper is to study the impact of the phenomenon of overconfidence and the disposition effect on the trading volume and their role in the formation of the excess volume on the Chinese stock market. We find a strong evidence of the overconfidence hypothesis. Besides, we show no evidence of the disposition effect on individual securities.

Key words: overconfidence, disposition effect, trading volume, emergent market

JEL classification: G11; G12

INTRODUCTION

According to the traditional finance theory (Fama, 1960) markets are efficient and investors have rational expectations and take decisions that maximize their expected utility. Nevertheless, some puzzles found on the financial markets, which previously could not be solved using this traditional theory, are accounted for once overconfidence of investors was assumed. These issues include excessive trading volume. Several studies consider the proposition that investor overconfidence generate the high trading volume observed in financial markets¹ (De Bondt and Thaler, 1995), Odean (1998a, 1998b, 1999), Gervais and Odean (2001)). These models predict that overconfident investors trade more than rational investors. De Bondt and Thaler (1995) argue that “the key behavioural factor needed to understand the trading puzzle is overconfidence”. Overconfident investors overestimate the precision of their own valuation abilities, in the sense that they overestimate the precision of their private information signals (Daniel et al., 1998, 2004; Gervais and Odean, 2001).

Researchers develop theory and testable implications under two assumptions. First, that investors are overly overconfident about the precision of their private information, and second, that biased self attribution causes the degree of overconfidence to vary with realised market outcomes.

There is no obvious ideal way to measure overconfidence² (Deaves et al., 2008). According to Glaser and Weber (2007), overconfidence can manifest itself in four facets: miscalibration (Lichtenstein et al., 1982; Vate, 1990; Keren, 1991; McClelland and Bolger, 1994), better than average (Svenson, 1981; Taylor and Brown, 1988), illusion of control (Langer, 1975; Presson and Benassi, 1998) and unrealistic optimism (Weinstein, 1980). The calibration technique is the one that most closely conforms to the new overconfidence models (Deaves et al., 2008).

¹ Contrary to that, Varian (1989) finds that trading volume is entirely driven by differences of opinions.

² Individuals are asked to construct 90% confidence intervals for currently (or soon) knowable magnitudes, a percentage of individuals usually markedly below 90% produce intervals that bracket the true answer.
Statman et al., (2006) report that there is little difference in the trading patterns implications between the miscalibrationversion of overconfidence and the better than average one (the idea that most investors simply believe their investment skills are better than average).

Statman et al., (2006) argue that investor overconfidence is a driver of the disposition effect\(^3\) (the tendency to sell winners too early and ride losers too long), because overconfidence encourages investors to trade asymmetrically between gains and losses. Overconfidence differs from the disposition effect in two ways. First, the disposition effect refers to an investor’s attitude towards a specific stock in the portfolio (Odean, 1998b; Rangelov, 2001; Dhar and Zhu, 2002. However, overconfidence affects the stock market in general. Second, the disposition effect explains the motivation for only one side of a trade. In contrast, overconfidence can explain both sides of a given transaction.

Many studies predict a link between current volume and lagged returns in the developed markets (Statman et al., 2006; Chuang and Lee, 2006; Glaser and Weber, 2007), but we find little evidence in emergent markets (Griffin et al., 2007; Chen et al., 2007). Furthermore, compared to developed markets, emerging markets are considerably smaller and less liquid. This death of liquidity can play an important role in determining the relationship between stock returns and trading volume; it can potentially alter the previous findings of the developed markets (Pisesitasalasi and Gunasekarage, 2006). The goal of our paper is to study overconfidence and the disposition effect and their correlations with trading volume in the Chinese market. Empirically, we use monthly data in order to correlate past market (security) returns with market (security) trading activity. Through the use of a threshold vector autoregression, we find that past market returns affect trading activity of individual investors. Thus, overconfident investors trade more than the others.

**Literature review**

Black (1986) argued that noise traders offer an exit from no-trading equilibrium of perfectly rational models of security markets. Odean (1998) and Gervais and Odean (2001) explained that overconfidence of noise traders increases trading volume as they attribute high returns in bull markets to their trading skills.

Odean (1998b) assumes that traders, insiders and market makers may unconsciously overestimate the precision of their information and rely on it more than is warranted, while traders display a better than average effect, evaluating their information as better than that of their peers. Such overconfidence market participants cause an increase in the trading volume. The same results are demonstrated by Benos (1998) in his model of an auction market with informed traders, where again the participation of risk-neutral investors overestimating the precision of their information leads to an increased trading volume.

Daniel et al., (1998) propose a model of overconfidence and biased self-attribute of investors, i.e. people overestimate the degree to which they are responsible for their own success, where security market under and overreactions follow respectively public and private signals.

According to Glaser and Weber (2007), at the individual level, overconfident investors will trade more aggressively: the higher the degree of overconfidence of an investor, the higher her or his trading volume. Odean (1998b) calls this finding “the most robust effect of overconfidence”. Glaser and Weber (2007) explain that as long as past returns are a proxy for overconfidence, these models postulate a positive lead-lag relationship between past returns and trading volume. The intuition behind this link is that high total market returns make investors overconfident about the precision of their information. Investors mistakenly attribute gains in wealth to their ability to pick stocks. As a result they underestimate the variance of stock returns and trade more frequently in subsequent periods because of inappropriately tight error bounds around return forecasts. Furthermore, Odean (1998b) shows that overconfident traders choose a riskier portfolio than would hold without overconfidence.

Gervais and Odean (2001) assume that overconfident traders realise, on average, lower gains, as they increase both trading and volatility, which in turn negatively affect trading results. They show that greater overconfidence leads to higher trading volume and that this suggests that trading volume will be greater after market gains and lower after market losses.

Hirshleifer and Luo (2001) explain the persistence of overconfidence on the market by the fact that overconfident traders are more aggressive than their rational counterparts in exploiting mispricings brought about by noise or liquidity traders. As a result, they trade aggressively due to two effects: their underestimation of risk and overestimation of own trading strategies.

Barber and Odean (2001) use gender as a proxy for overconfidence. They confirm that overconfident traders (men) in their sample\(^5\) trade more than women. As a result, the performance of men is hurt more by excessive trading. Barber and Odean (2002) analyse trading volume and performance of a group of 1,600 investors\(^6\) who switched from phone based to online trading during the sample period. They find that those who switch to online trading perform well prior to going online and beat the market.

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\(^3\) See Shefrin and Statman (1985) and Weber and Camerer (1998) for further empirical and experimental evidence on the disposition effect.

\(^4\) See Wolosin et al., (1973), Langer and Roth (1975), Miller and Ross (1975) and Schneider et al., (1979).

\(^5\) They use trading records of over 35,000 US households taken from a nationwide brokerage firm.

\(^6\) They use a data set from a US discount broker.
Furthermore, they find that trading volume increases and performance decreases after going online.

Chuang and Lee (2006) use data of US listed companies in the period 1963-2001, to prove a variety of effects of overconfidence on financial markets. They confirm the assumption of Gervais and Odean (2001), that trading profits induce overconfident investors more frequently to trade. In addition, Chuang and Lee (2006) provide support for investors displaying a self attribution bias for high market volatility being due to the presence of investor overconfidence, and for overconfident investors being prone to trade more in relatively riskier securities, after experiencing market gains.

Statman et al., (2006) test the market trading volume prediction of formal overconfidence models using US market level. They find that monthly market turnover (proxy of trading volume), is positively related to lagged market returns. Vector autoregression and associated impulse response functions indicate that individual security turnover is positively related to lagged market returns as well as to lagged returns of the respective security. Kim and Nofsinger (2007) confirm these findings using Japanese market level data. They identify stocks with varying degrees of individual ownership to test the hypothesis and discover higher monthly turnover in stocks held by individual investors during the bull market in Japan.

Griffin et al. (2007) investigate the dynamic relation between market wide trading activity and returns in 46 countries. Many stock markets exhibit a strong positive relation between turnover and past returns. This relation is much stronger for developing countries than for developed ones. These findings hold when they control for volatility, alternative definitions of turnover, differing sample periods, and are present at both weekly and daily frequency. They find also that this relation is more statistically and economically significant in countries with restrictions on short sales, where corruption is higher, and where the allocative efficiency of the stock market is weaker. The return-volume relation is also stronger for individual investors than for institutional or foreign investors.Chou and Wang (2011) examine a unique dataset obtained from the Taiwan Futures Exchange which records all account-level trades and orders. They differentiate empirically between overconfidence and disposition effect and demonstrate that different types of traders exhibit different types and levels of behavioral biases.

Lin (2011) utilizes the disposition coefficient to verify whether the disposition effect exists in Taiwan and Chinese stock markets during the periods of financial crises, and to discuss the differences of the disposition effect between appreciation and depreciation periods. The empirical results show that during the 1997 Asian financial crisis, the disposition effect significantly exhibits in the both markets. On the other hand, during the 2008 global financial crisis, the disposition effect only exhibits in Chinese stock market. Nevertheless, there are no significant differences of disposition effect between A-shares and B-shares.

Prosad and al., (2013) find that biases like the disposition effect and overconfidence prevail in Indian equity market and can lead to an increase in trading volume at market level as well as at individual security level.

Hypothesis

In order to examine how trading activity relates to lagged returns, we will test the following hypothesis:

**H1:** Trading volume is positively related to lagged market returns.

The positive trading volume response to lagged market returns is consistent with the overconfidence hypothesis. In fact, high market returns make investors overconfident about the precision of their private information. As a result, they trade more frequently which leads to high volume. As with Odean (1998) and Gervais and Odean (2001), we predict a positive lead-lag relationship between past market returns and trading volume.

**H2:** Individual security turnover is positively related to both lagged security and lagged market returns.

The positive security trading volume response to own lagged return is consistent with the disposition effect. In fact, the disposition effect indicates investors' tendency to enjoy realizing gains on individual security and to defer the combustion of losses (Shefrin and Statman, 1985). We predict a positive relationship between security trading and past market returns.

**H3:** Existence of a positive contemporaneous relationship between trading volume and volatility.

Large branch of theoretical and empirical research (Karpoff, 1987; Harris and Raviv, 1993; Shalen, 1993) relate volume to concurrent return volatility. We predict a positive contemporaneous relationship between trading volume and volatility.

**DATA AND METHODOLOGY**

Our database consists of monthly observations of Chinese Shenzhen & composite common stocks from January 2000 to December 2006. The data is obtained from Datastream. We focus on monthly observations under the perspective that changes in investor overconfidence occur over monthly or annual horizons (Odean, 1998b; Gervais and Odean, 2001; Statman et al., 2006). Following Lo and Wang (2000) and Statman et al., (2006), we measured trading activity with

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7 They characterize the overconfidence hypothesis by four testable implications.

8 The Shenzhen Stock Exchange was established in April 1991. This market exhibit strong growth in the past decade, and when combined with the Shangai Stock Exchange, are currently the ninth largest in the world (about 1,250 listed companies, with total market capitalization exceeding 653.50 billion USD).

9 We use monthly observations for trading volume and returns, but our estimate of volatility is constrained by the availability of daily returns.
turnover (shares traded divided by outstanding shares) and aggregate security turnover into market turnover on a value-weighted rather than equal-weighted basis. We use also another proxy (the volume), to measure the trading volume.

Figure 1 and 2 present trading volume approximated respectively by volume (shares traded) and turnover, from January 2000 to December 2006. An examination of long-term Chinese trading volume indicates that the volume has increased over the last two years. The increase of transactions can be explained by the existence of noise traders.

**Definition of variables**

- **Mrret**: the monthly stock market return with dividends
- **mtrading**: the monthly market turnover (shares traded divided by outstanding shares) or the monthly volume (shares traded).
- **msig**: the monthly temporal volatility of market return based on daily market returns within the month, correcting for realized autocorrelation, as specified in French, Schwert and Stambaugh (1987). The volatility according to French, Schwert and Stambaugh (1987) is calculated as follow: 
  \[
  Msig^2 = \sum_{t=1}^{T} r_t^2 + 2 \sum_{t=1}^{T} r_t r_{t-1},
  \]
  where \( r_t \) is day \( t \)'s return and \( T \) is the number of trading days in month \( t \); and this in order to adjust the first order autocorrelation of returns. This volatility control variable is based on Karppoff's (1987) survey of research on contemporaneous volume–volatility relationship, as is similar to the mean absolute deviation (MAD) measure in the trading volume study of Bessembinder, Chan and Seguin (1996). According to French, Schwert and Stambaugh (1987), non synchronous trading of securities causes daily portfolio returns to be autocorrelated, particularly at lag one. However, the negative sign of variance in the case of some individual securities leads us to use the approximation of Duffe (1995) \( Msig^2 = \sum_{t=1}^{T} r_t^2 \). In fact, French, Schwert, and Stambaugh (1987) approximation results in a negative variance estimate if the first-order autocorrelation of daily returns in a given month is \( \leq -0.5 \).

**Summary statistics**

The Table 1 provides summary statistics on monthly market return and market trading as well as a market-wide based control variable: volatility, during the period 2000-2006.

To test for unit root, we employ the ADF and Phillips-Peron (PP test) for all variables. The test results indicate that the null hypothesis that the variables are non stationary is strongly rejected except for the variables turnover and volume. Previous studies report strong evidence of both linear and non-linear time trend in trading volume series (Gallant et al., 1992; Chen et al., 2001). However, these linear time trend detrending methodologies appear not flexible enough for time series (Statman et al., 2006). We employ the Hodrick-Prescott (1997) algorithm (HP) for detrending the trading variable. In fact, the use of non stationary series can lead to bias in the coefficient standard errors of vector autoregression we employ in this study.

Hodrick-Prescott (HP) algorithm is a two sided linear filter that computes the smoothed series \( S \) of \( y \) by minimizing the variance of \( y \) around \( S \), subject to a penalty that constrains the second difference of \( S \). Specifically, The HP filter chooses \( S_t \) to minimize:

\[
\min_{S} \sum_{t} (y_t - S_t)^2 + \lambda \sum_{t} (S_t - S_{t-1})^2.
\]

11 A great advantage of PP test is that it is non-parametric, i.e. it does not require to select the level of serial correlation as in ADF. It rather takes the same estimation scheme as in DF test, but corrects the statistic to conduct for autocorrelations and heteroscedasticity.
12 For brevity tests of stationarity are not reported.
13 We use the natural log transformation before detrending the series. According to Statman et al. (2006), this can help eliminating the correlation between the level of the trend and volatility around the trend.
The penalty parameter $\lambda$, controls the smoothness of the series $S_t$. The larger the $\lambda$, the smoother the $S_t$. As $\lambda \rightarrow \infty$, $S_t$ approaches a linear trend. Our motivation for detrending is to extract a stationary time-series, not to predict the trend.

To test the normality of returns, we refer to Skewness and Kurtosis statistics. For market return, the Skewness is $\neq 0$ (0.77) and the Kurtosis is $\neq 3$ (4.89). This implies the non-normality of the distribution of returns.

**Empirical methodology**

Following Statman et al., (2006) we use a vector autoregression (VAR) and impulse response functions in order to study the interaction between market returns and trading proxies (turnover and volume). We use the following form of the VAR model:

$$Y_t = a + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_{t-l} + e_t$$  \hspace{1cm} (2)

where,
- $Y_t$: a (nx1) vector of endogenous variables (return and trading proxy: turnover and volume).
- $X_t$: a (nx1) vector of an exogenous variable: volatility.
- $e_t$: a (nx1) residual vector. It captures the contemporaneous correlation between endogenous variables.
- $A_k$: the matrix that measures how trading proxy and returns react to their lags.
- $B_l$: the matrix that measure how trading proxy and returns react to month (t-1) realizations of the exogenous variable.

Table 1: Market descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Return (mret)</th>
<th>turnover</th>
<th>volume</th>
<th>Detrended log turnover(mret)</th>
<th>Detrended log volume(mvol)</th>
<th>Volatility(msig)</th>
<th>Dispersion(Disp)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0001</td>
<td>0.0049</td>
<td>1.09E+16</td>
<td>2.38E-08</td>
<td>3.57E-08</td>
<td>0.0604</td>
<td>0.0037</td>
</tr>
<tr>
<td>Std Dev</td>
<td>0.0030</td>
<td>0.0030</td>
<td>1.19E+16</td>
<td>0.3776</td>
<td>-0.4166</td>
<td>0.0280</td>
<td>0.0016</td>
</tr>
<tr>
<td>Min</td>
<td>-0.0068</td>
<td>0.0011</td>
<td>4.13E+16</td>
<td>-0.8084</td>
<td>-0.7636</td>
<td>0.0172</td>
<td>0.0014</td>
</tr>
<tr>
<td>Max</td>
<td>0.0077</td>
<td>0.0150</td>
<td>5.08E+16</td>
<td>0.9881</td>
<td>1.0634</td>
<td>0.1643</td>
<td>0.0096</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.1540</td>
<td>1.3334</td>
<td>0.8429</td>
<td>0.3222</td>
<td>0.2860</td>
<td>1.2703</td>
<td>1.2905</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.6025</td>
<td>4.4461</td>
<td>3.1138</td>
<td>2.4944</td>
<td>2.4175</td>
<td>4.7373</td>
<td>4.5926</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>0.8852</td>
<td>32.2144</td>
<td>9.9927</td>
<td>2.3485</td>
<td>2.3332</td>
<td>33.1580</td>
<td>32.1965</td>
</tr>
<tr>
<td>Prob</td>
<td>0.6423</td>
<td>0.0000</td>
<td>0.0067</td>
<td>0.3090</td>
<td>0.3114</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

$$\sum_{t=1}^{T}(y_t-S_t)^2 + \lambda \sum_{t=1}^{T}[(S_{t+1}-S_t) - (S_t - S_{t-1})]^2$$ \hspace{1cm} (1)

$K$ and $L$: numbers of endogenous and exogenous observations. $K$ and $L$ are chosen based on the Akaike (1974) (AIC) and Schwartz (SC) information criteria\(^{14}\). In our case, the SIC leads to $K = 5^{15}$ and $L = 2$. Glaser and Weber (2009) note that overconfidence models are not very precise on how we should specify the lag length in empirical studies. Statman et al., (2006) find that returns that are lagged more than 6 months do not significantly affect trading activity anymore. Then, we employ impulse response functions to aggregate over coefficient estimates and illustrate how the endogenous variables relate to each other over time (Hamilton, 1994). Impulse response functions trace the effect of a one standard deviation shock in one residual to current and future values of the endogenous variables through the dynamic structure of the VAR.

Equation (3) contains two endogenous variables (market turnover or market volume) and an exogenous variable (volatility):

$$mtrading_{t} = \begin{bmatrix} mtrading_{t-1} + e_{mtrading_{t}} \end{bmatrix} + \begin{bmatrix} \alpha_{mtrading} \alpha_{mret} \end{bmatrix} + \begin{bmatrix} \sum_{k=1}^{5} A_k \end{bmatrix} + \begin{bmatrix} \sum_{i=0}^{2} B_i \end{bmatrix} + \begin{bmatrix} \sum_{i=0}^{2} \text{msg}_{t-i} \end{bmatrix} + \begin{bmatrix} \sum_{i=0}^{2} \text{e}_{mtrading_{t-i}} \text{e}_{mret_{t-i}} \end{bmatrix} \hspace{1cm} (3)$$

Changes in one residual, say $e_{mtrading_{t}}$, will immediately change the current value of mtrading, but will also affect the coefficient matrix of future values of mtrading and mret since lagged values of mtrading appear in both equations through the coefficient matrix $A_k$.

To test overconfidence, we shock the market return by one sample standard deviation and we track how market trading activity responds over time to the market return residual. We introduce the market return ($mret$) in the VAR model of individual securities, in order to check if disposition effect explains high trading volume as well as the overconfidence.

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\(^{14}\) We follow the common practice of setting $\lambda = 14,400$ for monthly observations.

\(^{15}\) The detrended time series used in this study is the monthly difference between log trading and its trend.

\(^{16}\) Our choice is based on the Schwartz information criterion (SIC) (we choose the number of lags which minimize the SIC).

\(^{17}\) Chuang and Lee (2006) chose also 5 lags for their model.
hypothesis. For that, we use a trivariate VAR model for each security with 3 endogenous variables: security trading volume, market return and security return; and a single exogenous variable, security volatility:

\[
\begin{bmatrix}
\text{trading}_{it} \\
\text{ret}_{it} \\
\text{mret}_t
\end{bmatrix} = \begin{bmatrix}
\alpha_{\text{trading}} \\
\alpha_{\text{ret}} \\
\alpha_{\text{mret}}
\end{bmatrix} + \sum_{k=1}^{6} A_k \begin{bmatrix}
\text{trading}_{i,t-k} \\
\text{ret}_{i,t-k} \\
\text{mret}_{t-k}
\end{bmatrix} + \sum_{l=0}^{\infty} B_l \text{sig}_{i,t-l}
\]

\[t + j + \begin{bmatrix}
\text{e}_{\text{trading}, t} \\
\text{e}_{\text{ret}, t} \\
\text{e}_{\text{mret}, t}
\end{bmatrix}
\]

(4)

Where,
- \( \text{trading}_{it} \): trading volume of the security \( i \) at month \( t \);
- \( \text{ret}_{it} \): return of the security \( i \) at month \( t \);
- \( \text{mret}_t \): volatility of the security \( i \) at month \( t \) based on the approximation of Duffe (1995).

As with the model, we are concerned with how security trading response to shocks in returns, both security return and market wide return. We introduce security return in order to test the overconfidence predictions of Daniel et al. (1998). If overconfidence explains volume in addition to disposition effect, we should find a positive relation between past market return and security trading volume even when lagged security returns are introduced in the model (Hypothesis 2).

### Market VAR estimation and test results

#### Market vector autoregression

Table (2) and (3) provide the results of equation (3). The variable \( \text{mtrading} \) in Table (2) represent volume. However, in Table (3), it represents turnover. The tables are organised by rows for each endogenous variable (\( \text{mret} \) and \( \text{mtrading} \)) and by columns for lagged ones. For each coefficient, we report the estimated value, t statistic and the standard errors.

From the Table (2.1), we document that market trading is autocorrelated, with a significant one lag coefficients. However, Lagged observations of trading volume are not correlated to market return.

The Table (2.2) presents the association between market volume and lagged market returns (hypothesis 1 of our study). We remark that volume is positively related to lag market returns with only one significant coefficient (the first lag). This result is consistent with previous empirical studies of overconfidence hypothesis (Statman et al. (2006), Griffin et al. (2007), Chuang and Lee (2006) and Glaser and Weber (2007)). According to Glaser and Weber (2007) and Deaves et al. (2007), high market returns make the investors overconfident in the sense that they underestimate the variance of stock returns. However, Hilary and Menzelt (2006) attribute this finding to the self attribution bias. In fact, investors think that their predictions are better than the others.

The Table (2.3) presents the relation between endogenous and the exogenous variable (\( msig \)). Results
show a positive and significant contemporaneous association between volume and volatility (Hypothesis 3). Our finding is consistent with Karpoff (1987) and Statman et al. (2006). In Table 3, we replace volume by turnover as a proxy of trading volume. We find the same results than those in Table 2. In fact, the relation between turnover and lagged market returns is also significant with one lag significant coefficient. We still show a positive and significant contemporaneous association between volume and volatility. However, market trading is not autocorrelated.

**Market impulse response functions**

Individual VAR coefficient estimates do not capture the full impact of an exogenous variable observation. An impulse response functions use all the VAR coefficient estimates to trace the full impact of a residual shock that is one sample standard deviation from zero.

Figure 3 contains all four possible impulse response function graphs using the bivariate VAR estimation shown in Table 2 and (3). The vertical axis measures the percentage increase in mtrading. We note that impulse response functions are forced to zero over time because mtrading proxy is detrended.

Figures (3a) and (3b) represent responses of mret to one standard deviation of mret and mtrading along with confidence bands spaced out at two standard errors. In Figure (3a), the impulse response function indicates that impact of mret shock is positive and persistent for about 5 months. Figure (3b) indicates that a one standard deviation shock to mtrading increases slightly, but, in general, the impulse response function coefficients are not significantly different from zero.

Figures (3c) and (3d) represent responses of mtrading to one standard deviation of mret and mtrading along with

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**Table 2.3. Relations with lagged volatility**

<table>
<thead>
<tr>
<th></th>
<th>constante</th>
<th>mSIGt-4</th>
<th>mSIGt-3</th>
<th>mSIGt-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>mtrading</td>
<td>-0.145655</td>
<td>3.447162</td>
<td>-1.866322</td>
<td>0.942678</td>
</tr>
<tr>
<td></td>
<td>(0.16473)</td>
<td>(1.65121)</td>
<td>(1.75059)</td>
<td>(1.71001)</td>
</tr>
<tr>
<td>mrett</td>
<td>-0.000177</td>
<td>-0.010395</td>
<td>0.004455</td>
<td>0.002211</td>
</tr>
<tr>
<td></td>
<td>(0.00131)</td>
<td>(0.01314)</td>
<td>(0.01393)</td>
<td>(0.01361)</td>
</tr>
<tr>
<td></td>
<td>[0.13498]</td>
<td>[-0.79110]</td>
<td>[0.31983]</td>
<td>[0.16248]</td>
</tr>
</tbody>
</table>

( ): Standard errors; []: t stat; *: coefficient significant at the level of 5%

**Table 3. Market VAR estimation (mtrading = turnover)**

**Table 3.1. Relations with lagged market trading**

<table>
<thead>
<tr>
<th></th>
<th>mtradingt-1</th>
<th>mtradingt-2</th>
<th>mtradingt-3</th>
<th>mtradingt-4</th>
<th>mtradingt-5</th>
</tr>
</thead>
<tbody>
<tr>
<td>mtrading</td>
<td>0.254712</td>
<td>-0.039198</td>
<td>-0.051835</td>
<td>-0.232996</td>
<td>-0.040423</td>
</tr>
<tr>
<td></td>
<td>(0.14496)</td>
<td>(0.14861)</td>
<td>(0.14032)</td>
<td>(0.13911)</td>
<td>(0.12776)</td>
</tr>
<tr>
<td></td>
<td>[1.75715]</td>
<td>[-0.26377]</td>
<td>[-0.36941]</td>
<td>[-1.67487]</td>
<td>[-0.31640]</td>
</tr>
<tr>
<td>mrett</td>
<td>-0.000332</td>
<td>-0.000126</td>
<td>-3.24 E-05</td>
<td>0.000270</td>
<td>4.04 E-05</td>
</tr>
<tr>
<td></td>
<td>(0.00049)</td>
<td>(0.00049)</td>
<td>(0.00049)</td>
<td>(0.00052)</td>
<td>(0.00052)</td>
</tr>
<tr>
<td></td>
<td>[-0.67223]</td>
<td>[-0.25585]</td>
<td>[-0.06631]</td>
<td>[0.51873]</td>
<td>[0.07713]</td>
</tr>
</tbody>
</table>

( ): Standard errors; []: t stat; *: coefficient significant at the level of 5%

**Table 3.2. Relations with lagged market return**

<table>
<thead>
<tr>
<th></th>
<th>mrett-1</th>
<th>mrett-2</th>
<th>mrett-3</th>
<th>mrett-4</th>
<th>mrett-5</th>
</tr>
</thead>
<tbody>
<tr>
<td>mtrading</td>
<td>33.25628</td>
<td>5.552437</td>
<td>6.0711434</td>
<td>25.18450</td>
<td>10.67140</td>
</tr>
<tr>
<td></td>
<td>[2.04126]*</td>
<td>[0.32514]</td>
<td>[0.35613]</td>
<td>[1.511833]</td>
<td>[0.65575]</td>
</tr>
<tr>
<td>mrett</td>
<td>0.33483</td>
<td>0.164771</td>
<td>0.147434</td>
<td>0.350943</td>
<td>0.130137</td>
</tr>
<tr>
<td></td>
<td>(0.14700)</td>
<td>(0.15408)</td>
<td>(0.15382)</td>
<td>(0.14966)</td>
<td>(0.14683)</td>
</tr>
<tr>
<td></td>
<td>[0.22778]</td>
<td>[1.06941]</td>
<td>[0.95849]</td>
<td>[2.34497]</td>
<td>[0.88632]</td>
</tr>
</tbody>
</table>

( ): Standard errors; []: t stat; *: coefficient significant at the level of 5%

---

18 Individual coefficients on lagged mSIG must be interpreted with caution because of autocorrelation in volatility (Gallant, Rossi and Tauchen, 1992; Chen, Firth and Rui, 2001).
Table 3.3. Relations with lagged volatility

<table>
<thead>
<tr>
<th></th>
<th>constante</th>
<th>mSig1</th>
<th>mSig1-1</th>
<th>mSig1-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>mtradingt</td>
<td>-0.222766</td>
<td>3.540842</td>
<td>-1.330508</td>
<td>1.415441</td>
</tr>
<tr>
<td></td>
<td>(0.15065)</td>
<td>(1.49311)</td>
<td>(1.59087)</td>
<td>(1.57408)</td>
</tr>
<tr>
<td>mret1</td>
<td>[-1.47872]</td>
<td>[2.37145]*</td>
<td>[-0.83634]</td>
<td>[0.89922]</td>
</tr>
<tr>
<td></td>
<td>(0.00136)</td>
<td>(0.01347)</td>
<td>(0.01435)</td>
<td>(0.01420)</td>
</tr>
<tr>
<td></td>
<td>[-0.04440]</td>
<td>[-0.74592]</td>
<td>[0.32373]</td>
<td>[0.40910]</td>
</tr>
</tbody>
</table>

(): Standard errors; []: t stat; *: coefficient significant at the level of 5%

Response to Cholesky One S.D. Innovations ± 2 S.E.

**Figure 3a:** Response of mret to mret

**Figure 3b:** Response of mret to mtrading1

**Figure 3c:** Response of mtrading1 to mret

**Figure 3d:** Response of mtrading1 to mtrading1

Figure 3: Market impulse response function with two-standard error bands (mtrading = volume)

Confidence bands spaced out at two standard errors. Figure (3.c) indicates a positive response in mtrading to mret shock; the key finding of this study. Figure (3.d) indicates a large and persistent response in mtrading to an mtrading shock.

When we use turnover as proxy of trading volume, we observe that Figure 4 is very similar to Figure 3.

Security VAR estimation and test results

Security vector autoregressions

In the previous section, we find evidence for overconfidence hypothesis in that market wide trading activity is positively related to past market returns by using VAR model and impulse response function. In fact, as explained by Statman et al. (2006), investors may be...
trading more after high market returns because of an increased confidence in their trading skills, or simply because they enjoy realizing paper gains on individual securities. Alternatively, investors may be trading less after negative market returns because the loss reduces their confidence in the value of trading, or simply because they do not want to sell individual securities and acknowledge the loss.

The estimation of equation (4) for each stock provides a voluminous output. For brevity, we report in Tables 4 and 5 cross sectional mean coefficient and associated t-stat. If the disposition hypothesis (hypothesis 2 of our study) is confirmed, security trading must be positively related to both lagged security and market returns.

Table (4) and (5) provide the results of equation (4). The variable mtrading in Table (4) represent volume. However, in Table (5), it represents turnover. The tables are organised by rows for each endogenous variable (ret, mret and mtrading) and by columns for lagged ones. For each coefficient, we report the estimated value and t-statistic. Contrary to Statman et al., (2006) we remark from table 4 and 5 that the relation between lagged coefficient of security returns and mtrading is positive for all the lags when (mtrading = volume), except the third lag. However, this relation is non significant. This relation is also non significant when we use as trading proxy the turnover. On the other hand, security trading volume is not related to past market returns. This result is evidence of the invalidation of the disposition effect hypothesis (Hypothesis 3).

To check robustness, we focus on the reaction of security trading volume to both lagged and market returns using impulse response functions. The results indicate that the response of security to market returns is not significant of the totality of our sample. This confirms that the disposition effect does not hold at monthly horizons in the Chinese market.

**Conclusion**

In this study, we analyse the overconfidence and the disposition hypothesis in the Chinese market using vector autoregression (VAR) and associated impulse response functions. We first document the overconfidence hypothesis. We find an evidence for this hypothesis. In fact,
Table 4. Security VAR estimation (trading = volume)

Table 4.1. Relations with lagged security trading

<table>
<thead>
<tr>
<th></th>
<th>trading₁</th>
<th>trading₂</th>
<th>trading₃</th>
<th>trading₄</th>
<th>trading₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>trading</td>
<td>0.2887</td>
<td>0.0749</td>
<td>0.0167</td>
<td>-0.0774</td>
<td>0.0673</td>
</tr>
<tr>
<td></td>
<td>(0.2173)</td>
<td>(0.0671)</td>
<td>(0.0173)</td>
<td>(-0.0712)</td>
<td>(0.0802)</td>
</tr>
<tr>
<td>ret</td>
<td>-4.51 E-05</td>
<td>-2.62 E-04</td>
<td>-3.69 E-04</td>
<td>-1.03 E-03</td>
<td>3.36 E-04</td>
</tr>
<tr>
<td></td>
<td>(-0.0058)</td>
<td>(-0.0230)</td>
<td>(-0.0494)</td>
<td>(-0.1210)</td>
<td>(0.0446)</td>
</tr>
</tbody>
</table>

() : t stat

Table 4.2. Relations with lagged security return

<table>
<thead>
<tr>
<th></th>
<th>ret₁</th>
<th>ret₂</th>
<th>ret₃</th>
<th>ret₄</th>
<th>ret₅</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0734)</td>
<td>(-0.0326)</td>
<td>(0.0658)</td>
<td>(0.0436)</td>
<td>(-0.124)</td>
</tr>
<tr>
<td>ret</td>
<td>-0.2191</td>
<td>-0.1885</td>
<td>-0.0015</td>
<td>-0.0284</td>
<td>-0.0703</td>
</tr>
<tr>
<td></td>
<td>(-0.109)</td>
<td>(-0.161)</td>
<td>(-0.0052)</td>
<td>(-0.0421)</td>
<td>(-0.0615)</td>
</tr>
</tbody>
</table>

() : t stat

Table 4.3. Relations with lagged market return

<table>
<thead>
<tr>
<th></th>
<th>mret₁</th>
<th>mret₂</th>
<th>mret₃</th>
<th>mret₄</th>
<th>mret₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>mtrading</td>
<td>49.0881</td>
<td>8.4621</td>
<td>-18.1815</td>
<td>8.9233</td>
<td>-12.3918</td>
</tr>
<tr>
<td></td>
<td>(0.1346)</td>
<td>(0.0334)</td>
<td>(-0.0627)</td>
<td>(0.0275)</td>
<td>(-0.0601)</td>
</tr>
<tr>
<td>mret</td>
<td>0.1680</td>
<td>0.1388</td>
<td>-0.0281</td>
<td>0.1102</td>
<td>0.0884</td>
</tr>
<tr>
<td></td>
<td>(0.2134)</td>
<td>(0.1174)</td>
<td>(0.0138)</td>
<td>(0.0842)</td>
<td>(0.0332)</td>
</tr>
</tbody>
</table>

() : t stat

Table 5. Security VAR estimation (trading = turnover)

Table 5.1. Relations with lagged security trading

<table>
<thead>
<tr>
<th></th>
<th>trading₁</th>
<th>trading₂</th>
<th>trading₃</th>
<th>trading₄</th>
<th>trading₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>trading</td>
<td>0.2658</td>
<td>0.0646</td>
<td>0.0029</td>
<td>-0.1006</td>
<td>0.0397</td>
</tr>
<tr>
<td></td>
<td>(0.2314)</td>
<td>(0.0590)</td>
<td>(0.0037)</td>
<td>(-0.0988)</td>
<td>(0.0473)</td>
</tr>
<tr>
<td></td>
<td>(0.0068)</td>
<td>(-0.029)</td>
<td>(-0.0325)</td>
<td>(-0.119)</td>
<td>(-0.0390)</td>
</tr>
</tbody>
</table>

() : t stat

Table 5.2. Relations with lagged security return

<table>
<thead>
<tr>
<th></th>
<th>ret₁</th>
<th>ret₂</th>
<th>ret₃</th>
<th>ret₄</th>
<th>ret₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>trading</td>
<td>0.9032</td>
<td>-11.5954</td>
<td>5.1608</td>
<td>5.2665</td>
<td>-5.4548</td>
</tr>
<tr>
<td></td>
<td>(0.0065)</td>
<td>(-0.0691)</td>
<td>(0.0278)</td>
<td>(0.0247)</td>
<td>(-0.0359)</td>
</tr>
<tr>
<td>ret</td>
<td>-0.2173</td>
<td>-0.1922</td>
<td>-0.0088</td>
<td>-0.0491</td>
<td>-0.0902</td>
</tr>
<tr>
<td></td>
<td>(0.0107)</td>
<td>(0.0678)</td>
<td>(0.0301)</td>
<td>(0.166)</td>
<td>(0.0319)</td>
</tr>
</tbody>
</table>

() : t stat

Table 5.3. Relations with lagged market return

<table>
<thead>
<tr>
<th></th>
<th>mret₁</th>
<th>mret₂</th>
<th>mret₃</th>
<th>mret₄</th>
<th>mret₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>trading</td>
<td>46.2690</td>
<td>6.0147</td>
<td>-11.3007</td>
<td>6.7732</td>
<td>-8.3615</td>
</tr>
<tr>
<td></td>
<td>(0.1447)</td>
<td>(0.0237)</td>
<td>(-0.0382)</td>
<td>(0.0217)</td>
<td>(-0.0386)</td>
</tr>
<tr>
<td>mret</td>
<td>0.1610</td>
<td>0.1489</td>
<td>-0.0240</td>
<td>0.1154</td>
<td>0.0987</td>
</tr>
<tr>
<td></td>
<td>(0.1928)</td>
<td>(0.1223)</td>
<td>(-0.0285)</td>
<td>(0.1120)</td>
<td>(0.0943)</td>
</tr>
</tbody>
</table>

() : t stat
past market returns affect trading activity only when the trading proxy used is volume over some months. Then, we document the association between security trading volume and past market returns. Contrary to the results of Statman et al. (2006), we find no evidence of the disposition effect of Shefrin and Statman (1987). Finally, we find a contemporaneous significant positive relation between volume and volatility. This result holds on aggregated and security levels. The predictability of security returns based on lagged volume has been documented by many financial economists as a possible violation of strict market efficiency (Karpoff, 1987; Gallant et al., 1992; Zhao and Wang, 2003; Yin, 2010; Wang and Huang, 2012).

As future research, it would be interesting to use daily data (Chorida et al., 2007) or weekly ones (Griffin et al., 2007) to study the impact of the phenomenon of overconfidence and the disposition effect on the trading volume. It would also be important to see which past returns affect trading volume (past market returns or past portfolio returns (Glaser and Weber, 2009). Finally, future empirical research can also distinguish between individual and institutional investors (Cho and Kyooosung, 2006; Ben-David and Doukas, 2006; Sankar et al., 2011).

REFERENCE