Trading Shocks, Asset Prices, and the Limits of Arbitrage

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Abstract

This paper examines the relationship between trading shocks and asset prices. We outline a simple market clearing model in which some investors place orders that are uncorrelated with asset fundamentals. Our empirical results show pervasive price pressure at a daily, weekly and monthly frequency. We sort stocks into deciles based on trading shocks. Initial distortions in the extreme deciles are over 200bp and prices take five weeks to mean-revert back to pre-shock levels. Our model predicts that trading in one stock can affect prices of other stocks. Empirically, we find support for the model and show that the temporary price impact doubles during periods when many stocks experience similarly-signed shocks. Finally, trading shocks are able to explain approximately 50% of observed stock return co-movement. Our results provide insights into the limits of arbitrage and a market's ability to absorb demand shocks.

Keywords: Asset pricing, return predictability, limits of arbitrage

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1 Introduction

Does uninformed trading affect asset prices? According to traditional asset pricing theory, trading that is not related to asset fundamentals does not move prices outside transaction cost boundaries. In an arbitrage pricing theory framework, many fully diversified arbitrageurs instantly detect mispricings, tap into an infinite pool of capital, and counterbalance the actions of uninformed traders. In equilibrium asset pricing models, prices are set by a fully diversified representative investor. The representative investor aggregates available information and then eliminates mispricings by continuously adjusting her portfolio.

Over the past two decades evidence has accumulated that demand shocks may actually affect prices. The majority of such evidence comes from studies of large, low frequency events such as additions to, deletions from, or re-balancing of stock indices.[1] Despite the accumulation of such evidence, questions surrounding uninformed trading do not appear to be settled empirically. Recent papers such as Denis, McConnell, Ovtchinnikov, and Yu (2003) question whether index re-balancing is actually an information-free event. Hedge and McDermott (2003) question whether index re-balancing changes stocks' liquidities. Others, such as Mitchell, Pulvino, and Stafford (2004) who study price pressure around mergers, conclude that it is appropriate to assume the demand curves for stocks "are horizontal in most situations."

Our paper takes a new approach by studying the trading of normal stocks on normal days. The shift away from rare, index re-balancing events produces two contributions of our paper. The first concerns our model. In it, optimizing agents take into account the fact that trading shocks are likely to occur in the future. Our approach is fundamentally different from models such as Greenwood (2005a, 2005b) in which the agents do not condition on the possibility that others will demand liquidity in the future.[2] The second contribution concerns our empirical section. We identify *ex-ante* a large fraction of individual trades that we believe are unrelated to fundamental information about the underlying stocks. Micro-structure data confirm that these trades are liquidity demanding (as opposed to providing liquidity to other market participants.) Simple overview statistics support the notion that the trades carry little to no information: a replicating portfolio based on our trades produces a negative alpha of 5% per year before transaction costs. Only after the initial identification do we test the

[1]See Harris and Gurel (1986); Shleifer (1986); Kaul, Mehrotra, and Morck (2000); Wurgler and Zhuravskaya (2002); and Greenwood (2005a) for some examples.

[2]The approach taken in Greenwood (2005a) makes sense when studying a one-time index re-balancing under the assumption that the re-balancing is *unforeseen* by all rational agents.

implications of our model with our data. Our approach avoids the circularity involved when one identifies non-informational trades with a specific model, and then tests the model with the same data.

1.1 Related Studies

Our paper can be compared to, and contrasted with, two recent strands of research that approach questions relating to non-informational trading and asset prices from two separate directions. The common theme in both strands is the use of actual trading data.[3]

Large data samples from exchanges: Griffin, Harris, and Topaloglu (2003) study all trades in the Nasdaq 100 stocks over a nine-month period. The authors looks at the daily trading behavior of individuals and institutions. Their results differ markedly from ours. They find a strong positive contemporaneous correlation between institutional buying and returns. They find no evidence that imbalances predict future daily returns. Their findings support the idea that institutions help incorporate information into prices.

Kaniel, Saar, and Titman (2004) study the daily dollar volume of buys and sells by individual investors of NYSE stocks. Like Griffin, Harris, and Topaloglu (2003), they find individuals buy stocks that have recently fallen and sell stocks that have recently risen. Unlike the earlier study, Kaniel, Saar, and Titman (2004) show that stocks that individuals buy outperform stocks they sell by 30 bp to 67 bp per week. The authors conclude the "patterns are consistent with the idea that risk-averse individuals provide liquidity to meet institutional demand." While the magnitude of the weekly returns is similar to our paper, the sign is opposite. One possible difference is that Kaniel, Saar, and Titman (2004) condition on trades that are not observable to all market participants, while the trades in our paper are publicly available. Second, the authors do not find strong evidence of correlated trading across stocks when using a principal component analysis; we do. Finally, and most likely, our results differ from results Kaniel, Saar, and Titman (2004) due to institutional features of the NYSE order

[3]There is a related literature that uses indirect measures to study the link between investor behavior (often called "investor sentiment") and asset prices. One such literature looks at closed-end fund premiums and discounts. Well known papers in this area are: Lee, Shleifer, and Thaler (1991); Sias, Starks, and Tinic (2001); Gemmill and Thomas (2002); and Bodurtha, Kim, and Lee (1995). Others, such as Neal and Wheatley (1998), look at measures of sentiment, such as mutual fund redemptions and the odd-lot ratio in addition to closed-end premiums/discounts. Lee, Jiang, and Indro (2002) study the Investors Intelligence sentiment index. Baker and Wurgler (2003) use a combination of measures. Analogously, work on index additions has generally focused on price movements rather than trading in the underlying shares.

routing system. As Harris (2005) pointed out, brokers filter trades from individual investors. Trades that are likely to be uninformed are routed to local exchanges. Trades that may contain information are more likely to get routed to the NYSE floor, which is exactly the data used by Kaniel, Saar, and Titman (2004). Trades in our study are not filtered by an order routing system.

Data from a retail brokerage firm: A few recent papers use data from a large retail brokerage firm. For example, Goetzmann and Massa (2003) study the relationship between the disposition effect (the propensity of investors to sell winners and hold losers) and cross-sectional variation in asset prices. They use actual trades from retail investor accounts to construct stock-level measures. Exposure to a "factor" based on investor trading helps explain the cross-section of returns. Kumar and Lee (2004) calculate monthly order imbalances for each stock traded in the data. They sort stocks into deciles based on the imbalance to create a factor in a cross-sectional asset pricing model. The returns of small stocks have a positive loading on their factor. Goetzmann and Kumar (2004) construct a "diversification measure" for each stock based on the level of diversification of individuals in their dataset. Returns of small stocks (as well as low book-to-market stocks) load positively on their factor.

The main difference between our paper and papers that use the retail brokerage data is scope. The retail data has six years of history (1,500 trading days) and contains approximately one million transactions. Assume U.S. investors have access to 5,000 different stocks. These numbers imply researchers observe trades in 13% of the 7.5 million stock-day combinations—*at most*. By contrast our dataset contains aggregated daily trades for approximately one million stock-day combinations. Of these, approximately 95% are non-zero. We turn now to a brief overview of our research design.

1.2 Research Design

Our paper has three goals. The first is to derive the testable implications of a model in which rational agents account for the possibility of future trading shocks. The second goal is to test the price pressure implications in the case of a single stock. We refer to these tests "time-series results" since we are concerned with the price path of a single stock over time. Our third goal is to test the cross-stock implications of our model. Specifically, we are interested in the impact that trading in Stock A has on the price of Stock B. The existence of cross-stock effects can have market-wide implications. For example, price pressure can be exacerbated on days when many stocks have similarly-signed trading shocks. In other words, the market's ability to absorb/provide liquidity in a single asset (stock) is influenced by simultaneous demands across other assets.

As mentioned in the previous sub-section, existing papers that study actual trades are hampered by lack of data, order routing procedures, and/or sparsely populated samples. To get around such problems, our paper proposes a new identification method that allows us to study trading in all stocks, for a given stock market, on a daily basis, and over an eight year period. We explore a unique feature of the Taiwanese Stock Exchange (TSE) that allows us to identify a large sample of trading demands. We are able to achieve this identification by studying long margin holdings and the associated changes in these holdings. Unlike most other stock markets, the TSE publicly reports the number of shares held long on margin for each stock, on a daily basis (i.e., aggregated at the day-stock level.)

It is estimated that 99.3% of our data is generated by individuals. Readers can think of the following analogy: our data represent a fraction of all individual trading; index funds represent a fraction of all institutional trading. Identification does not come from the fraction represented. Rather, identification comes from having a well-defined sample of investors from which financial economist can sign trades. Most importantly, micro-structure data from Taiwan shows that approximately 80% of margin trades can be classified as aggressive.[4] The trades are noisy at the stock level. A representative portfolio based on our data turns over multiple times each year, yet underperforms the market by approximately 5% per year before transaction costs. Interestingly, these trades by individuals investors do not "wash out" and there are large net buy/sell imbalances at a daily, weekly, and monthly frequency. In addition, we measure a significant common component of uninformed trading across stocks.

While our research design has the advantage of allowing us to see the signed imbalance of daily trades across all stocks, there are a few drawbacks. First, our data are not from the United States. Readers who are not familiar with Taiwan may be initially uneasy. Second, our identification is different from typical studies of index re-balancing. Third, this paper does not investigate the coordinating component behind the trading shocks. Instead, we study the impact on asset prices.[5] Some might think of the underlying traders as sentiment traders or noise traders. Such an interpretation complements papers such as Lee, Shleifer, and Thaler (1991); Delong et. al. (1990); and Black (1986). Others may think of the trade

[4] Barber, Lee, Liu, and Odean (2005) generously classify trades for us using their micro-structure data.

[5] We do rule out obvious forces that may generate our data. For example, our data are not correlated with margin lending rates nor are they correlated with short-term rates such as the six month money market rate in Taiwan. Investors in our sample do not appear to be using margin accounts to hold levered positions in the overall market.

data as exogenous liquidity or non-informational demands as in Campbell, Grossman, and Wang (1993). In this alternative view, our results speak directly to a market's ability to absorb demand shocks.

We believe the advantages of using our data far outweigh the disadvantages. At the same time, we pay particular attention to the drawbacks mentioned above. We test numerous, alternative hypotheses. We split our data by frequency, time-period, and stock subsample. Our results paint a consistent picture—uninformed trading shocks have large, temporary effects on prices. While one can think of a story that might explain part of our results, we know of no economic framework (other than the model presented in this paper) that can explain all of our results.

Our paper now proceeds as follows: Section 2 outlines a simple model with two types of traders: a) optimizing agents; and b) investors who place inelastic orders that are uncorrelated with underlying fundamentals. Section 3 describes the data used in this paper and gives some overview statistics. Section 4 presents the time series results—i.e., results relating to price pressure and mean reversion. Section 5 tests the cross-stock implications of our model. Results include finding a single common factor in uninformed shocks (across stocks) and measuring the impact of trading in Stock B on the price of Stock A. Section 6 provides a number of additional checks. Section 7 concludes.

2 A Model of Trading Shocks

To study the possible relationship, if any, between trading shocks and asset prices we provide a simple adaptation of the Campbell, Grossman, and Wang (1993) model—hereafter referred to as "CGW (1993)". Note that the original authors use their model to study the relationship of returns and a measure of *unsigned* volume; our paper looks at the relationship between returns and a *signed* measure of net trades. Our model also borrows features from the model in DeLong et. al (1990)—hereafter referred to as "DSSW (1990)." We specify that a fraction of investors place inelastic orders for shares. These investors have no information about fundamental values. All three models—CGW (1993), DSSW (1990), and ours—specify that remaining investors (optimizing agents) have limited risk-bearing capacity and myopic horizons.

2.1 Set-Up of Model

There is a riskfree asset with gross return R and a risky asset (a stock) that pays a stochastic dividend D_t each period. The riskfree asset is in unlimited supply and its price is fixed at one. The supply of the stock is one. Dividends follow an $AR(1)$ process such that: $D_t = \overline{D} + \widetilde{D}_t$; with $\widetilde{D}_t = \alpha_D \cdot \widetilde{D}_{t-1} + u_{D,t}$; and $u_{D,t} \overset{iid}{\sim} N(0, \sigma_D^2)$. At each time t, there is a noisy public signal S_t about $u_{D,t+1}$. We stick with the CGW (1993) notation that $S_t \sim N(0, \sigma_s^2)$; with $u_{D,t+1} = S_t + \varepsilon_{D,t+1}$; $\varepsilon_{D,t+1} \sim N(0, \sigma_\varepsilon^2)$; and $E[u_{D,t+1}|S_t] = S_t$. The time t price of the stock is denoted by P_t, and its excess return at time $t+1$ is defined as:

$$Q_{t+1} \equiv P_{t+1} + D_{t+1} - RP_t$$

The model contains optimizing investors with $CARA$ utility and risk aversion coefficient a. Following CGW (1993), those traders are assumed to maximize next period wealth. The proportion of the utility-maximizing investors in the market is fixed at ω. Their total demand for the stock is denoted ωX_t:

$$\omega X_t = \omega \left(\frac{1}{a} \cdot \frac{E_t[Q_{t+1}]}{Var_t[Q_{t+1}]} \right) \tag{1}$$

In the spirit of Black (1986) and DSSW (1990), the model also has uninformed investors, in proportion $1 - w$. Their total demand is denoted by $\aleph_t$:

$$\aleph_t \equiv (1 - \omega) Z_t$$

We assume Z_t, the variable part of uninformed investors' demand, follows an $AR(1)$ process: $Z_t - \overline{Z} = \alpha_z \left(Z_{t-1} - \overline{Z} \right) + u_{z,t}$; and $u_{z,t} \overset{iid}{\sim} N(0, \sigma_u^2)$. A difference between our model and DSSW (1990) is the restriction that α_z be less than one. This restriction ensures excess returns are stationary . The market clearing condition is:

$$\omega X_t + (1 - \omega) Z_t = 1$$

At time t, the risk-neutral cum-dividend fundamental value of the risky asset is F_t. This value is defined as the expected present discounted value of all future dividends (conditional on information known at time t). It can be shown that:

$$F_t = \left(\frac{R}{R-1} \right) \overline{D} + \left(\frac{R}{R - \alpha_D} \right) \widetilde{D}_t + \left(\frac{1}{R - \alpha_D} \right) S_t$$

The variance of innovations in the fundamental value is:

$$\sigma_F^2 = \left(\frac{R}{R-\alpha_D}\right)^2 \sigma_\epsilon^2 + \left(\frac{1}{R-\alpha_D}\right)^2 \sigma_S^2$$

If $(2a(1-w))^2 \sigma_F^2 \sigma_u^2 \leq 1$, there is a rational expectations equilibrium in which the price function has the following linear form:

$$P_t = F_t - D_t + q_0 + q_z Z_t$$

where q_0 is a constant and q_z is a constant greater than zero. Denote the variance of excess returns by σ_Q^2. It can be shown that: $\sigma_Q^2 = \sigma_F^2 + q_z^2 \sigma_u^2$.

2.2 Testable Implications of the Model

It is convenient to define both the change of the proportion of stock held by noise traders and the percent (or relative) change in these holdings:

$$\begin{aligned} \Delta\aleph_t &= (1-\omega)(Z_t - Z_{t-1}) \\ \%\Delta\aleph_t &= \frac{Z_t}{Z_{t-1}} - 1 \end{aligned} \tag{2}$$

We now relate changes in the proportion of stock held by uninformed traders to contemporaneous excess returns:

$$Cov(\Delta\aleph_t, Q_t) = (1-\omega)\, q_z\, (1+R) \left(\frac{\sigma_u^2}{1-\alpha_z^2}\right)(1-\alpha_z) > 0 \tag{3}$$

We also relate percent change in uninformed holdings to contemporaneous excess returns:

$$Cov(\%\Delta\aleph_t, Q_t) = q_z \left(\frac{\sigma_u^2}{1-\alpha_Z^2}\right)\left((R-\alpha_z)\cdot g\left(\overline{Z}, \alpha_z, \sigma_u^2\right) + (1-\alpha_z)\cdot E\left[\frac{1}{Z_t}\right]\right) > 0 \tag{4}$$

where $g\left(\overline{Z}, \alpha_z, \sigma_u^2\right)$ is a positive function. Equation (3) shows that a positive shock to the proportion of the stock held by uninformed traders tends to increase the same-period excess return. Similarly, Equation (4) shows that the correlation between the percentage increase in uninformed holdings and contemporaneous returns is also positive. In other words, both measures of net changes to uninformed trader holdings ($\Delta\aleph_t$ and $\%\Delta\aleph_t$) are positively correlated with contemporaneous returns.

We next look at predictable changes to future returns. We see a negative relationship between uninformed trading this period and excess returns next period (again using either measure of change):

$$\begin{aligned} Cov\left(\Delta\aleph_t, Q_{t+1}\right) &= -(1-\omega)q_z\left(R-\alpha_z\right)\left(\frac{\sigma_u^2}{1-\alpha_z^2}\right)(1-\alpha_z) < 0 \\ &and \\ Cov\left(\%\Delta\aleph_t, Q_{t+1}\right) &= -q_z\left(R-\alpha_z\right)\left(\frac{\sigma_u^2}{1-\alpha_z^2}\right) g\left(\overline{Z}, \alpha_z, \sigma_u^2\right) < 0 \end{aligned} \tag{5}$$

In fact, for any future period ($j \geq 1$), we see an exponentially declining covariance between uninformed trading this period and future returns.

$$\begin{aligned} Cov\left(\Delta\aleph_t, Q_{t+j}\right) &= -(1-\omega)q_z\left(R-\alpha_z\right)\left(\frac{\sigma_u^2}{1-\alpha_z^2}\right)(1-\alpha_z)\alpha_z^{j-1} < 0 \\ &and \\ Cov\left(\%\Delta\aleph_t, Q_{t+j}\right) &= -q_z\left(R-\alpha_z\right)\left(\frac{\sigma_u^2}{1-\alpha_z^2}\right) g\left(\overline{Z}, \alpha_z, \sigma_u^2\right)\alpha_z^{j-1} < 0 \end{aligned} \tag{6}$$

Both parts of Equation (5) show that either a positive shock to the proportion of the stock held by uninformed investors, or a percentage increase in these holdings, is linked to a decrease in the excess return over subsequent periods. In other words, increases in net buying today should predict negative future returns. And Equation (6) shows this effect decays exponentially with the number of periods after the shock. Finally, Equations (5) and (6) imply that one can use changes in uninformed holdings ($\Delta\aleph_t$) and/or the percentage change in uninformed holdings ($\%\Delta\aleph_t$) as conditioning variables to predict future returns. We elaborate more on empirical issues and identification in Section 3.

2.3 A Two-Asset Extension

We extend the model by adding a second risky asset. For simplicity, we model the second asset much like the first one: dividends follow an AR(1) process, etc. We specify that the parameters of the two dividend processes are the same and the shocks are uncorrelated. Thus, the fundamental values of the two assets are uncorrelated.

The uninformed investors have demands Z_t^A and Z_t^B for the two assets. The demands are inelastic and the variable parts follow AR(1) processes. We allow the shocks to the two demands $\left(u_{z,t}^A \text{ and } u_{z,t}^B\right)$ to be correlated with parameter ρ. This simple, two-asset specification allows us to think of a market-wide (undiversifiable) component to uninformed investor shocks whenever $\rho > 0$. The rational expectations equilibrium prices of the two assets have the form:

$$\begin{aligned} P_t^A &= F_t^A - D_t^A + q_0^A + q_z^{AA} Z_t^A + q_z^{BA} Z_t^B \\ P_t^B &= F_t^B - D_t^B + q_0^B + q_z^{AB} Z_t^A + q_z^{BB} Z_t^B \end{aligned}$$

Here, q_0^A and q_0^B are constants, q_z^{AA} is a constant relating the shock of uninformed trading in Stock A to the price of Stock A, q_z^{AB} is a constant relating the shock of uninformed trading in Stock A to the price of Stock B, and so on.

Despite the simplicity of the model, we are unable to get closed-form solutions for the equilibrium prices of the two risky assets. We are, however, able to obtain numerical solutions as well as show that the model collapses to the single-asset model when ρ equals zero. Appendix 1 gives additional notes. There are two testable implications. The first is that a positive trading shock in Stock B has a positive price impact on Stock A; also a positive trading shock in Stock A has a positive price impact on Stock B:

$$q_z^{BA} > 0 \qquad\qquad q_z^{AB} > 0 \tag{7}$$

The second implication is that the magnitude of the cross effects are increasing in ρ:

$$\frac{\partial q_z^{BA}}{\partial \rho} > 0 \qquad\qquad \frac{\partial q_z^{AB}}{\partial \rho} > 0 \tag{8}$$

3 Data

We obtain data with the help of a national securities firm in Taiwan and a data provider called the Taiwan Economic Journal (TEJ). Time series consist of daily holdings, stock prices, returns, and share information at the individual stock level. The full sample contains information on 647 different listed companies in Taiwan. Some companies delist and others appear throughout our sample period. Approximately thirty companies have return data but no holdings data. The maximum number of contemporaneously listed companies reaches 598 between 12-Jun-2002 and 19-Jul-2002. The full sample period begins 5-Jan-1994 and ends 29-Aug-2002. Thus, the sample consists of 2360 holding/trading days or 443 calendar weeks.

3.1 Data and Overview Statistics

Price, return, and data: We obtain share prices, returns, and number of shares outstanding for each listed stock at both daily and weekly frequencies. Data are available from the TEJ. Daily and weekly returns are adjusted for capital changes. Figure 1 shows the market index over our sample period.

Holdings Data: The most interesting part of our data are margin holdings. We obtain the daily number of shares held long on margin for 608 listed stocks. The number of shares are reported to the TSE by brokerage firms. The aggregate number of shares held long on margin for each listed stock is available each day from the TSE on the exchange's website, and from other data providers such as the TEJ. We define the long margin holding of company "i" at time "t" to be:[6]

$$H_{i,t} \equiv \frac{\text{shares held long on margin}_{i,t}}{\text{total shares outstanding}_{i,t}} \tag{9}$$

Some stocks have no margin holdings data for long periods of time, even though they are listed and continue to trade. Therefore, we run all tests on the full sample of data and a subsample of firms for which margin data exists over the entire 1994 to 2002 period. Justification for using a subsample and examples of data gaps are given in Appendix 2. The average holding level across stocks is defined as:

$$H_{EW,t} \equiv \frac{1}{N} \sum_i H_{i,t} \tag{10}$$

Figure 2 plots average long margin holdings over time. While long margin positions typically account for 6% to 12% of shares outstanding (on average), there is a dip to the 4% to 6% range starting in year 2000. We make sure our results are robust over different time periods. There is little difference between the full sample of 608 firms and the subsample of 131 firms.

Net Changes to Holdings (Net Trading): From the holdings data we calculate the net change in shares held long on margin. For a given stock we know by how much investors

[6] We would like to observe the proportion of uninformed investors in the market multiplied by their average demand, Equation (2). Instead, we observe the fraction of a company's shares held on margin. Readers can think of the observable quantity as a proxy for $\aleph_{i,t}$, plus some noise that is uncorrelated with the random variables of the model. It is reasonable to regard the variance of this noise as small because the uninformed traders hold and trade a sizable fraction of shares outstanding. Normalizing holdings by shares outstanding is also useful when comparing across stocks.

increased or decreased their long margin holdings.[7] We define two slightly different measures of changes to holdings. The first measure is[8]

$$\Delta H_{i,t} \equiv \frac{\text{shrs held long}_{i,t} - \text{shrs held long}_{i,t-1}}{\text{tot shrs outstanding}_{i,t}} \tag{11}$$

The second measure is equal to the percentage change in $H_{i,t}$ if the total number of shares outstanding doesn't change over the period. It is defined as

$$\%\Delta H_{i,t} \equiv \frac{\text{shares held long on margin}_{i,t}}{\text{shares held long on margin}_{i,t-1}} - 1 \tag{12}$$

From Equation (2) of our model, we see that $\Delta H_{i,t}$ and $\%\Delta H_{i,t}$ compare with $\Delta\aleph_t$ and $\%\Delta\aleph_t$ from our model. Also notice that the measure $\%\Delta H_{i,t}$ goes to infinity as the number of shares held on margin goes to zero.[9] Due to the extreme values of $\Delta H_{i,t}$ and $\%\Delta H_{i,t}$, we winsorize subsample measures at their 0.5% and 99.5% daily and weekly values. This treatment leaves much of our analysis unaffected, since we employ a decile-based sort methodology. Figure 2 also shows auto-correlation in net trades. For the market as a whole, the daily auto-correlation coefficient of $\Delta H_{EW,t}$ is 0.46, which is much higher than the average value of 0.17 at the individual stock level.[10]

Overview Statistics: Table 1, Panel A shows cross-company measures of $H_{i,t}$, $\Delta H_{i,t}$, and $\%\Delta H_{i,t}$. Average holding levels are 0.0725, with a 0.0360 to 0.1049 intraquartile range. We see that uninformed trading (net changes to long positions) is volatile. The measure $|\%\Delta H_{i,t}|$ is 0.0237 at a daily frequency, and 0.0738 at a weekly frequency.

Table 1, Panel B shows time-series measures that compare directly to Figure 2. The unbalanced panel accounts for the disparity in average holding levels between Panel A and Panel B for the full sample of firms. For the balanced subsample of 131 companies, sample averages are equal across panels. There is further evidence that investors do not use margin accounts to hold a levered position in the market: holding levels do not move together. The

[7] Our data unfortunately do not contain the volume of long margin trades—we only have the net increases and decreases. Daily margin volume is currently available from the TSE, but only since 2000. Monthly volume numbers start in 1999. We do not have intraday trading data.

[8] Our measure is equivalent to defining: $\Delta H_{i,t} \equiv H_{i,t} - H_{i,t-1}$ on all days *except* days when the number of shares outstanding change. The definition we use helps keep days with an increase in total shares outstanding from appearing to be days when uninformed investors are selling.

[9] This property is further justification for using the subsample of firms.

[10] A table with the first three auto-correlation coefficients at both daily and weekly frequencies is available from the authors by request.

average pair-wise correlation of $\Delta H_{i,t}$ is significantly less than one: approximately 0.0449 for the daily full sample and 0.0937 for the weekly full sample.

3.2 Identification Trading Shocks

We employ a three-tiered methodology that involves ex ante identification of trading shocks. We find this methodology to be preferable to the circularity inherent in ex post identification — i.e., filtering trades (data) through an economic or statistical model and then carrying out tests with the same model.

Step 1—Sample Selection: We begin by choosing holdings and trades that we believe are generated by non-fundamental trading—in this case long margin positions. We believe *ex-ante* four things about the data: a) Reported margin holdings from the TSE come almost exclusively from individual investors; b) Individual investors have little to no information about stock fundamentals; c) Institutions that want to hold levered equity positions can raise money at rates at least as favorable as those offered by brokerage houses to retail investors; d) Individuals borrow money from their brokers to place market orders. Individuals do not borrow money to place limit orders that may or may not be executed in the future.[11]

Step 2—Simple Overview Statistics: We verify that our data do, in fact, match our beliefs by interviewing local brokers. We also asked a private party with access to transaction-level data to calculate the percentage of margin trades done through individual accounts. It is estimated that 99.3% of margin trades are from individuals. Most importantly, Barber et. al. (2005) have micro-structure data from Taiwan and generously offered to classify trades as either "aggressive" or "passive". Approximately 90% of all margin trades can be classified. Of these, approximately 80% can be classified as "aggressive". These statistics make us confident that margin trades are demanding liquidity (not supplying it) the vast majority of the time.

Existing literature also confirms our beliefs. Barber et. al. (2005) track all trades done by individuals in Taiwan from 1994 to 1999. They show individuals trade too much. Turnover is 300% to 600% per year, which reduces returns by 3.5% per year. As the authors point out, it is unlikely that rebalancing or hedging needs can account for this turnover. The same

[11] Technically, in Taiwan, all orders are limit orders. One can choose the limit price such that the order will be executed immediately. In this market, such orders are typically referred to as "marketable limit orders" or "aggressive orders".

point can be made more forcefully if one considers that a substantial fraction of individual trades in Taiwan are held for only a short period of time.

Margin holdings account for approximately 7.25% of shares outstanding. Yet margin trading can account for up to 40% of a given stock's monthly turnover. We check if the holdings mirror the overall market by forming a representative (mimicking) portfolio based on the aggregate number of shares in our dataset. We rebalance the portfolio at the end of each week and record the return over the following week. The mimicking portfolio underperforms the market by 10.449 bp per week, which is over 5% per annum. The underperformance of the mimicking portfolio is further support that the investors who generate our data are uninformed (i.e., there is little evidence that individuals are incorporating information into prices on average.)[12]

The volatility of tracking error (difference in returns between the mimicking portfolio and the market) is 1.106% per week. Such a large value indicates that margin investors (in aggregate) are not tracking the market. The mimicking portfolio has a market beta that is close to, but statistically more than one. Trading is also very noisy. The absolute value of the portfolio changes by 0.40% per week on average. But, the number of shares held per stock experiences an average absolute change of 5.04% per week. All of these overview statistics lead us to believe our sample of data represents a significant pool of uninformed trades.

Step 3—Ex-Post Testing of a Model (Mean Reversion): In Section 2 we outline a model of trading shocks and in Sectionn 2.2 we list some testable implications of that model. In Section 4 (below) we confirm that our data fits the predictions of the model.

Thus, our three step procedure involves ex-ante and ex-post identification of signed trading shocks. Additional explanations of the identification process are provided in Appendix 3. We turn now to testing the predictions of our model.

[12] One might hypothesize that there a few individuals in Taiwan use margin accounts to take levered positions in stocks for which they have private (inside) information. Since our data are aggregated at the day-stock level, we are concerned with the information of the average investor. Insider trading, if any, would only serve to bias results against finding price pressure.

4 Time-Series Results: Price Pressure and Mean Reversion

4.1 Regression Analysis—Contemporaneous Returns

We test if changes in margin holdings (signed trading shocks) are positively correlated with contemporaneous returns—see Equation (3). We run a pooled regression, across the 131 stocks, of returns ($r_{i,t}$) on a constant and contemporaneous $\Delta H_{i,t}$. We do this at both daily and weekly frequencies. As predicted, we find a strong positive relationship with a 44.65 t-statistic at the daily frequency and a 17.83 t-statistic at a weekly frequency. The t-stats are based on standard errors that allow for clustering of contemporaneous observations (i.e., across stocks, at the same point in time.)

One might worry that outliers overly influence the results of a linear regression. Therefore we also perform a non-parametric kernel regression of $r_{i,t}$ on $\Delta H_{i,t}$. For daily data we used a Gaussian kernel with a 0.0175% bandwidth. For weekly data we used a Gaussian kernel with a 0.0600% bandwidth. Results of both the linear and nonlinear specifications are shown in Figure 3. From the kernel regression, we see that the true relationship is not exactly linear, as implied by the model. Rather there is some asymmetry in the response of returns to positive and negative shocks to $\Delta H_{i,t}$. Also, extremely negative values of $\Delta H_{i,t}$ are not associated with as large a price decline as more moderately negative values.[13]

4.2 Regression Analysis—Next Period's Returns

We test if trading shocks are negatively correlated with future returns—see Equation (5). We run a regression of next period's returns $r_{i,t+1}$ on a constant and this period's $\Delta H_{i,t}$. We again do this at both a daily and weekly frequency. Also, we again perform a non-parametric kernel regression.

The graphs in Figure 4 lend additional support for the model presented in Section 2. The slope of the linear regression is significantly negative at all conventional levels. The daily and weekly regressions have -8.65 and -3.18 t-statistics respectively. We again report conser-

[13] Results are qualitatively unchanged when using different subsamples and measures. We test Equation (4) by regressing returns on contemporaneous $\%\Delta H_{i,t}$ and get similar t-statistics for the linear regression: 42.82 at a daily frequency and 16.86 at a weekly frequency. We use the full sample of 608 stocks and get a t-statistic of 52.73 at a daily frequency and 20.55 at a weekly frequency. All t-statistics are based on standard errors that allow for clustering of contemporaneous observations. If we use White standard errors, t-statistics are approximately three times higher.

vative t-statistics by allowing for clustering at each point in time (day or week.) The kernel regressions show similar flat sections around moderate changes of $\Delta H_{i,t}$. Yet a clear pattern emerges. Positive changes in $\Delta H_{i,t}$ are followed by negative returns next period. Negative changes in $\Delta H_{i,t}$ are followed by positive returns.[14]

4.3 Sorting Results—Contemporaneous and Future Returns

To further investigate the predictability shown in Figure 4 and Equation (5), we perform a simple sorting procedure. Each period we rank stocks based on changes in $\Delta H_{i,t}$. Stocks are then put into one of ten portfolios based on ranking. The lowest decile is called "Portfolio 1" and the $\Delta H_{i,t}$ of stocks in this portfolio usually has a negative sign, though not necessarily. Likewise, the highest decile is called "Portfolio 10" and the $\Delta H_{i,t}$ of stocks in this portfolio usually has a positive sign, though also not necessarily. The sort procedure effectively deals with concerns about outliers in our measure of trading activity. A non-parametric sort procedure allows for non-linear price pressure. Most importantly, the sort procedure allows us to quantify the economic significance of the predictability shown in Figure 4.

In Table 2, we measure the equal-weighted return to each of the ten portfolios (deciles) over the following period for the full sample of 608 stocks and the subsample of 131 stocks. Our procedure is very similar to the typical sorting methodology used in momentum studies. We report returns over the next day or week.

Stocks with low $\Delta H_{i,t}$ this period have high returns next period; stocks with high $\Delta H_{i,t}$ this period have low returns next period. We report results for a hypothetical zero-cost portfolio that goes long low $\Delta H_{i,t}$ stocks and short high $\Delta H_{i,t}$ stocks. On average, the zero-cost portfolio returns—labeled "difference 1-10" or "$r_1 - r_{10}$"—are between 32 and 42 bp per day and 55 to 72 bp per week. T-statistics indicate a high level of significance for all measures. The degree of predictability shown in Table 2 is quite surprising.[15]

While Table 2 only shows next-period returns, we track the zero-cost portfolio returns over

[14] Figure 4 remains qualitatively unchanged if we regress future returns on $\%\Delta H_{i,t}$. The t-statistics at the top of each of the two panels become -7.30 and -2.91 respectively. When using the full sample of 608 stocks, the t-statistics from Figure 4 become -5.06 and -2.01 respectively.

[15] We perform robustness checks of Table 2 in a number of dimensions. When using $\%\Delta H_{i,t}$ instead of $\Delta H_{i,t}$ the zero-cost portfolio earns 45 bp at a daily frequency (t-statistic=18.57) and 82 bp at a weekly frequency (t-statistic=6.20). We divide our data into four equal time periods and sort based on $\%\Delta H_{i,t}$. Returns to the zero-cost portfolio are significantly positive at the 5% level for all time periods. Note that reconciling the results of Table 2 with Figure 4 is difficult because the cutoff values for the portfolio bins change each period.

the next ten periods—thus we specifically address the testable implications shown in Equation (6). Figure 5 shows the cumulative returns to the zero-cost portfolio (inverted) for the subsample of 131 firms. We invert in order to aid intuition. Think of the graph as follows: at time zero, uninformed traders heavily buy (sell) a certain stock. The price shoots up (down) a combined total of 1.29% that day or 2.37% that week. Prices then start to mean-revert back to pre-shock levels. On the first day, prices fall (rise) 42 bp or during the first week prices fall (rise) 72 bp. The 42 bp and 72 bp are exactly the returns to the zero-cost portfolio shown in Table 2. The mean-reversion doesn't stop after only one period. Over the five to six weeks that follow the initial buying (selling), prices continue to fall (rise) toward pre-existing levels. The pattern of mean-reversion—specifically the exponential decline shown in Equation (6)—fits with predictions from our model.[16]

Following convention, we expand our sort methodology. We first condition on changes in uninformed positions over the previous J periods (days or weeks.) We then look at portfolio returns over the next K periods. Results are presented in Appendix 4. Note that when $J = 1$ we are only conditioning on the current day or week. When $J = 1$ and $K = 1$ the results are identical to those shown in Table 2 and Figure 5. When sorting on the past three weeks (approximately a month) the returns to the zero-cost portfolio rise to 171 bp over the next three weeks. These are gross returns and are not annualized. The largest per-period return clearly comes from the day or week immediately following portfolio formation.[17]

4.4 Risk-Adjusted Returns

We examine the correlation of the zero-cost portfolio with known and potential risk factors. In Table 3, we regress the excess weekly returns of the zero-cost portfolio on a constant and the market excess return. Regression 1 shows the "alpha" of the regression is 73 bp which is very similar to the 72 bp reported in Table 2. The market beta is low and not significantly different from zero. In Table 3 we also include Fama-French size and book-to-market factors as well as a Carhart momentum factor.[18] We note, however, that Chen and Zhang (1998) look at Taiwanese stock returns between 1976 and 1993 and conclude that neither size-

[16]Figure 5 makes it easy to see how little evidence there is of private information being incorporated (on average) into stock prices—as opposed to Kyle (1985). In fact, when we plot returns based on sorting by $\%\Delta H_{i,t}$ instead of $\Delta H_{i,t}$, cumulative returns mean-revert completely back to zero.

[17]Recent work by Easley, Hvidkjaer, and O'Hara (2004) provides a useful benchmark for assessing the economic magnitude of the zero-cost portfolio returns. The authors sort stocks into deciles based on their "PIN" measure (probability of informed trade). Their zero-cost portfolio earns an average 27 bp per month before transaction costs.

[18]Please see Appendix 5 for a description of factor construction.

sorted nor book-to-market-sorted zero-cost portfolios earn statistically significant profits. This is confirmed in Barber, Lee, Liu and Odean (2004), who show that profits of size, book-to-market, and momentum-sorted portfolios change sign in their 1983-2002 and 1995-1999 subsamples. Therefore, the evidence that SMB, HML and MOM are proxies for sources of systematic risk is very weak in Taiwan.

Table 3 shows that regression coefficients relating to possible factors are insignificant, except for beta on the momentum factor. We conclude that any negative serial correlation that exists in the market at a weekly frequency does not affect the risk-adjusted alpha of the zero cost portfolio. As can been in Table 3, Regression 5 the constant is 79 basis points (which is actually above the non-risk adjusted return of 72 basis points.) Additional tests, discussed in Section 6, show that the mean reversion is not the product of momentum, feedback trading, or volume-based strategies. The section also shows that returns cover transaction costs after an initial one-week holding period.

5 Cross-Stock Results

5.1 Cross-Stock Trading Shocks

We test if trading in Stock B has an increasingly large impact on the price of Stock A as the parameter ρ increases—see Equation (8). Remember that $\rho_{i,j}$ is the correlation of trading shocks across stocks in our model and discussed in Section 2.3: $\rho_{i,j} = corr\left(\Delta H_{i,t}, \Delta H_{j,t}\right)$. Our test has three parts.

Step 1: We measure the pair wise correlation for all pairs in our 131 stocks subsample.[19] The 131 stocks produce 8,515 pairs.

Step 2: We estimate the impact of trading in Stock B on the returns of Stock A. We use three different regressions specifications. In all three cases we are interested in the regression coefficient $\gamma_{i,j}$. The difference in the specifications depends on whether we use actual trading shocks $\Delta H_{j,t}$ or standardized shocks $\left(\Delta H^S_{j,t} = \frac{\Delta H_{j,t} - mean(\Delta H_{j,t})}{stdev(\Delta H_{j,t})}\right)$. We also

[19]The use of the subsample ensures that shocks are measured over the same time period and for the same length of time.

consider controlling for own trading shocks:

$$\begin{aligned} r_{i,t} &= \alpha + \gamma_{i,j} \Delta H^S_{j,t} + \varepsilon_t \\ r_{i,t} &= \alpha + \gamma_{i,i} \Delta H_{i,t} + \gamma_{i,j} \Delta H_{j,t} + \varepsilon_t \\ r_{i,t} &= \alpha + \gamma_{i,i} \Delta H^S_{i,t} + \gamma_{i,j} \Delta H^S_{j,t} + \varepsilon_t \end{aligned}$$

Step 3: We test Equation (8) directly by measuring the final correlation of our trading correlation coefficient (from Step 1) with our regression coefficient (from Step 2.) Note, it is not apriori obvious if the final correlation is positive. The correlation of the trading shocks ($\rho_{i,j}$) may not be positive. The cross-stock regression coefficient ($\gamma_{i,j}$) may not be positive.

Table 4 shows support for the implication in Equation (8). Even after controlling for own shocks (the γ_{ii} term), the average pair-wise correlation is positive. While pair-wise measurements fit our model exactly, we are actually interested in whether trading shocks hit many stocks simultaneously or not.

5.2 Market-Wide Trading Shocks

We test if many stocks face similar uninformed shocks at the same time. To do this, we extract the principal components from the correlation matrices of $\Delta H_{i,t}$ and $\%\Delta H_{i,t}$. We focus on the 131 stocks in our subsample and find the first principal component explains between 12.85% and 15.02% of normalized variance. These values are significant at all conventional levels. The results are shown in Figure 6. The second principal component only explains between 2.63% and 2.94% of the variance, the third only explains between 2.46% and 2.53%, and so on. This large first principal component can be thought of as a common, time-varying factor that is present in all stocks' uninformed trading.

We next test, for each stock, if $\Delta H_{i,t}$ loads positively on the first principal component.[20] Table 5, Panel A shows our results.[21] We find a positive loading for all 131 stocks. We also check stock return loadings on the first principal component of uninformed trading. We find returns of all 131 stocks load positively on the first principal component.

Since we know that stock returns and uninformed trading are positively correlated, we push the analysis further. We decompose the first principal component into a part that is parallel

[20] Here we use the first principal component derived from the correlation matrix of $\Delta H_{i,t}$, but we get very similar results when using $\%\Delta H_{i,t}$.

[21] While we measure loadings with regressions, we report correlation coefficients because they are easier to interpret.

to overall market returns and a part that is orthogonal. Table 5, Panel B shows our results. We find $\Delta H_{i,t}$ for all 131 stocks loads positively on the orthogonal part of the first principal component. Surprisingly, we find returns for 117 of the 131 stocks load positively on the orthogonal part as well. To summarize, our principal component analysis provides evidence that uninformed trading shocks may not cancel each other out. Thus, pair-wise cross-stock effects can accumulate.

5.3 The Price Response to Market-Wide Shocks

To test for cumulative cross-stock effects, we revisit the contemporaneous price impact analysis shown in Figure 3. In the weekly figure, the slope of the linear line is +2.68, indicating a price impact of 2.68% for every 1.00% change in uninformed holdings. We re-run the regression and interact the change in a firm's uninformed holdings with a new indicator variable ($I_{i,t}^{mkt}$) on the right-hand side. The indicator variable equals one ($I_{i,t}^{mkt} = 1$) if $\Delta H_{i,t}$ is positive, $\Delta H_{EW,t}$ is positive, and if $\Delta H_{EW,t}$ is in the top 25% of its empirical distribution. In other words, it is difficult for the optimizing investors to provide liquidity to the uninformed investors at times of marketwide liquidity shocks. For symmetry, the indicator variable equals one ($I_{i,t}^{mkt} = 1$) if $\Delta H_{i,t}$ is negative, $\Delta H_{EW,t}$ is negative, and if $\Delta H_{EW,t}$ is in the bottom 25% of its empirical distribution. In this situation, it is difficult for the market to absorb stock when many shares are being sold. The regression is:

$$r_{i,t} = \gamma_1 + \gamma_2 \left(\Delta H_{i,t}\right) + \gamma_3 \left(\Delta H_{i,t} \cdot I_{i,t}^{mkt}\right) + \gamma_4 \left(sign \left|\Delta H_{i,t}\right|^2\right) + \varepsilon_{i,t} \tag{13}$$

The results from (13) are shown in Table 6 and are surprising. In Regression 1 we see the 2.68 slope shown in Figure 3. In Regression 3, $\gamma_2 = 3.16$ with a 14.95 t-statistic while γ_4 is significantly negative due to the concave shape shown in the kernel regression part of Figure 3. Most importantly, $\gamma_3 = 4.12$ with a 11.32 t-statistic. These results indicate that the impact of a trading shock is much higher when the market's ability to absorb/provide liquidity is diminished.[22] Clearly this result points to a number of avenues for future research. We discuss these avenues in the conclusion.

[22]We also run the regression with a signed exponential to take into account the curvature seen in Figure 3. Results are not changed.

5.4 Co-Movement

Recent work by Morck, Yeung, and Yu (2000) has focused attention on the co-movement of stocks—especially in emerging markets. The authors describe three plausible explanations for their findings. While we cannot do a cross-country comparison due to the lack of similar trading data from other countries, we can test what fraction, if any, of observed co-movement is explained by our trading shocks. To do this, we begin by measuring the R^2 on a stock-by-stock basis from the following equation:

$$r_{i,t} \quad = \quad \alpha + \beta r_{m,t} + \varepsilon_t$$

We then augment the regression with trading shocks and report results in Table 7. Specification 1 shows the average R^2 is 0.2958 using weekly data from the 131 firms in our subsample. In Specification 2, we orthogonalize the market return $r_{m,t}$ with respect to our market-wide measure of trading shocks ($\Delta H_{EW,t}$). Table 7, shows that our market-wide measure of trading shocks explains 49.25% of the co-movement.[23] Including a stock-specific measure of trading shocks ($\Delta H_{i,t}$) allows us to explain even higher fraction of variance.

We view the co-movement results in Table 7 as another way to present results relating to the principal component and positive factor loadings. If we were to have similar data from other countries, we could try to link the strength of the principal component to country-level variables such as investor protection. In this way, we might be able to provide additional insight into synchronous stock price movements.

5.5 Limits of Arbitrage and Narrow Framing

We test a final implication of our model. In Equation (1) we see that the demand of the optimizing investors is proportional to an expected Sharpe ratio. If prices are driven too far from fundamentals, the optimizing investors will step in until the expected Sharpe ratio of the zero-cost (risky) portfolio is reasonable. We perform a quasi-test using Figure 7. In Panel A we first plot the cumulative returns of the zero-cost portfolio, along with fixed transaction costs expressed in the same return units.[24] We see that holding the portfolio for at least two weeks is enough to cover direct costs. In Panel B, we include the iso-bars for four different after-cost Sharp ratios (plotted on the same time vs. pre-cost return axes we use in the

[23]From Table 7: $\frac{0.1582}{0.3212} = 49.25\%$. Alternatively, $\frac{0.1582}{0.3212} = 53.48\%$.

[24]Section 6.4 explains how we calculate transaction costs.

left-hand panel.) The steepest line shows the return needed to achieve an annual after-cost Sharpe ratio of 0.50 (holding the zero-cost portfolio for one week, two weeks, three weeks, etc.). The returns of the zero-cost portfolio are bounded above by an after-cost Sharpe ratio of 0.50 (approximately.)[25]

The results in Figure 7 are both comforting and puzzling. The returns to the zero-cost portfolio are bounded by a reasonable annual Sharpe ratio. Since we know the zero-cost portfolio has very low market exposure (Table 3) it is surprising that the optimizing investors do not compete to combine the zero-cost portfolio with the overall market portfolio. In other words, the annualized values of alpha shown in Table 3 remain high. One interpretation is that arbitrageurs engage in narrow framing. They see a stock get hit by a negative trading shock and they focus on buying that stock once its price falls a certain amount. They do not appear to be using a portfolio approach (i.e., buying a fraction of each stock that experiences selling pressure.)

6 Additional Tests

This paper uses Taiwanese data. We study demand shocks that are not related to index rebalancing. Since both the market and the identification may by new to readers, we believe it is prudent to provide a number of alternative tests. These tests lend additional support to our interpretation that observed stock returns patterns come from trading shocks.

6.1 Momentum in Returns

Does the zero-cost portfolio unintentionally measuring momentum (or reversals) in stock returns? No. Table 3 addresses this question directly. We can see that the zero cost portfolio loads negatively on the momentum factor. However, the statistical and economic significance of the alpha in the regression remains virtually unchanged.

We investigate further. It turns out that Taiwanese stock returns are, on average, positively auto-correlated at a daily frequency. We believe this effect is driven by small, low-priced stocks and the daily price limits that exist in this market. Accounting for positive auto-correlation at the daily frequency improves our results. In other words, we measure mean

[25]Holding the zero-cost portfolio for one week does not cover costs, thus the after-cost Sharpe ratio is negative. To achieve an after-cost Sharpe ratio of 0.30, the zero-cost portfolio would need to earn 100 bp, as seen in the figure.

reversion after accounting for the underlying positive serial correlation.

Taiwanese stocks have a zero or slightly negatively auto-correlation at the weekly frequency. Such auto-correlation might explain a fraction of our weekly results. However, the zero-cost portfolio shows consistent pattern of mean-reversion at both a daily and weekly frequency. Any explanation that relies on underlying return auto-correlation needs to explain why the sign of such auto-correlation changes but the sign of the mean-reversion remains consistent.

6.2 Feedback Trading Strategies

We test whether investors are following a feedback trading strategy and/or if momentum can explain our results. We employ a double-sort methodology in which we independently sort stocks into one of three $\Delta H_{i,t}$ bins (low, medium, and high) and one of three $r_{i,t}$ bins (low, medium, and high) for a total of nine bins.

Results are shown in Appendix 6, Panel A. Investors who follow a positive feedback trading strategy earn a very small return next period. This return is 17bp if confined to low $\Delta H_{i,t}$ stocks. The return is smaller if confined to medium- or high $\Delta H_{i,t}$ stocks.

By contrast, sorting stocks by $\Delta H_{i,t}$ leads to mean reversion of 30bp for medium $r_{i,t}$ stocks to 45bp for high $r_{i,t}$ stocks.[26] The consistent mean-reversion (after sorting by different return levels) again supports our findings.

6.3 Volume-Based Trading Strategies

Are our results an artifact of volume-based reversals as shown in CGW (1993)? To check this we do a double-sort methodology where we independently sort stocks into one of three $\Delta H_{i,t}$ bins (low, medium, and high) and one of three turnover bins (low, medium, and high) for a total of nine bins.

Appendix 6, Panel B shows our results. Strategies based on buying high turnover stocks and selling low turnover stocks earn 7 bp, -7 bp, and -12 bp for low, medium, and high $\Delta H_{i,t}$ stocks respectively. Thus the reversals predicted by CGW (1993) only exist in medium and high $\Delta H_{i,t}$ stocks, which is what the authors would expect if they could sign volume.

[26] The average return is less than the 72 bp reported in Table 3 because we are no longer using the top and bottom deciles.

Mean reversion based on sorting by $\Delta H_{i,t}$ is 32 bp, 14 bp, and 51 bp for low, medium, and high turnover stocks respectively. Again, the magnitude and consistent sign of these results supports our intepretation.

6.4 Transaction Costs

Are returns to the zero-cost portfolio large enough to cover transaction costs? Security firms in Taiwan are free to charge any commission they like as long as rates do not exceed 0.1425% of value traded. Large clients typically negotiate rates as low as 0.0700%. A dealer hoping to trade profitably against uninformed traders should only charge itself marginal cost which we, being conservative, estimate at 0.0700% of value. In addition, there is a 0.3000% tax levied on all sales. Thus, we estimate a round-trip transaction cost of 0.4400%. The round-trip cost on a zero-cost portfolio is 0.8800%. From Figure 7, Panel A we see that the a one week holding period return is about equal to transactions costs. Holding periods greater than a week are more than enough to cover transaction costs. A rough calculation based on earning 171 bp (pre-cost) over three weeks translates into over 15% per annum after costs.

6.5 Open Prices

If we form the zero-cost portfolio using the next period's open price, weekly returns of the zero-cost portfolio actually go up: from 55 bp to 65 bp (full sample) and from 72 bp to 78 bp (subsample).

6.6 Fama-McBeth Regressions

We re-estimate the linear regression coefficient of 2.6843 shown in Figure 3, Panel B and in Table 6, Regression 1 using Fama-McBeth methodology period by period. The time-series average coefficient from this second methodology is 1.2984 with a 11.7583 t-statistic. While smaller in magnitude than the earlier coefficient, results are still statistically significant at all conventional levels.

6.7 Consistent Explanations

The fact that our identification strategy uses margin trades leads many readers to believe that something related to leverage drives our results. For example, many readers hypothesize "when prices rise, margin traders have more buying power and they buy more stock." While this story is possible, we do not believe it would manifest itself on a daily frequency. More importantly, such a story only explains the contemporaneous correlation of returns and trading at an intra-day frequency. Such a story does not provide a consistent explanation for the future mean-reversion in prices. Nor does such a story provide any intuition for our cross-stock findings.

Likewise, explanations that margin traders buy in response to aggregate liquidity shocks are possible. However, for such a story to be consistent will all of our findings, aggregate liquidity shocks need to be correlated with a pricing kernel that induces massive mean-reversion in prices. We know of no such kernel. In short, we believe our model provides a concise, unified framework to explain the observed interaction of trading behavior and asset prices.

7 Conclusion

We explore a unique feature of the Taiwanese Stock Exchange that allows us to identify a large sample of demand shocks. We are able to achieve this identification by studying long margin holdings and the associated changes in these holdings. The holdings and behavior of the traders fits with our ex-ante beliefs about uninformed investors. Trades overwhelmingly come from individual investor accounts and these are exactly the investors who are known to be unprofitable. A portfolio that mimics aggregate margin trading behavior turns over many times each year and underperforms the market by about 5% per annum before transaction costs. Changes in margin holdings are volatile and do not track the market.

The data fit the predictions of a model in which some investors place inelastic orders that are uncorrelated with asset fundamentals. Buying by uninformed investors today is correlated with contemporaneous price increases. Selling today is correlated with contemporaneous price decreases. The correlation reverses itself over future periods. Prices reverse in an exponential pattern back toward fundamental values.

The data also fit our model's cross-stock predictions. We find an economically and statistically large common component of uninformed net trades across stocks. The net uninformed trades and returns of individual stocks all load positively on this component. In fact, net trades in individual stocks all load positively on the part of the common component that is orthogonal to market returns.

We began this paper by outlining our goal of testing for links between uninformed shocks and asset prices. However our results also give insight into the structure of markets. For example, the zero-cost portfolio designed to take advantage of uninformed trading does not earn unlimited profits. Instead, profits are bound above by an annualized 0.50 Sharpe ratio. Furthermore, the ability of the market to provide or absorb liquidity in a given stock is linked to net shocks across the rest of the market.

There are a number of directions that future research might take. A clear path is better understand the coordinating behavior behind the uninformed trading shocks. Are the individual investors themselves subject to common shocks? Future work can test if aggregate uninformed trades are correlated with macro-economic time series. Finally, future research can investigate what factors determine a market's ability to absorb/provide liquidity. In particular, we would like to investigate whether the price impact of uninformed trades varies with other macro-economic factors.

References

[1] Acharya, Viral V. and Lasse Heje Pedersen, 2004, "Asset Pricing with Liquidity Risk," forthcoming *Journal of Financial Economics*.

[2] Baker, Malcolm P. and Jeffrey Wurgler, 2005, "Investor Sentiment and the Cross-Sections of Stock Returns," *Journal of Finance* Forthcoming.

[3] Barber, Brad, Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2004, "Do Individual Day Traders Make Money? Evidence from Taiwan," Working paper, U.C. Davis.

[4] Barber, Brad, Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2005, "Who Losses from Trade? Evidence from Taiwan," Working paper, U.C. Davis.

[5] Berndt, Antje, Rohan Douglas, Darrell Duffie, Mark Ferguson, and David Schranz, 2004, "Measuring Default Risk Premia from Default Swap Rates and EDFs," Working paper, Cornell University.

[6] Black, Fischer, 1986, "Noise," *Journal of Finance*, 41, 3.

[7] Bodurtha, James N. Jr., Dong-Soon Kim, and Charles M. C. Lee, 1995, "Closed-end Country Funds and U.S. Market Sentiment," *Review of Financial Studies*, 8, 3, 879-918.

[8] Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, "Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns," *Journal of Financial Economics*, 49, 345-373.

[9] Brown, Stephen, William N. Goetzmann, Takato Hiraki, Noriyoshi Shiraishi, and Masahiro Watanabe, 2002, "Investor Sentiment in Japanese and U.S. Daily Mutual Fund Flows," Working paper, New York University.

[10] Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, "Trading Volume and Serial Correlation in Stock Returns," *Quarterly Journal of Economics,* 108, 4, Nov., 905-939.

[11] Chen, Nai-fu and Feng Zhang, 1998, "Risk and Return of Value Stocks," *Journal of Business*, 71, 4, October, 501-535.

[12] DeLong, Bradford, Andrei Shleifer, Lawrence Summers and Robert Waldman, 1990b, "Noise Trader Risk in Financial Markets," *Journal of Political Economy*, 98(4), 703-738.

[13] Denis, Diane K., John J. McConnell, Alexei V. Ovtchinnikov, and Yun Yu, 2003, "SP500 Index Additions and Earnings Expectations," *Journal of Finance*, LVIII(5), October, 1821-1840.

[14] Easley, David, Soren Hvidkjaer, and Maureen OHara, 2004, "Factoring Information into Returns," Working paper, Cornell University.

[15] Fishe, Raymond, Lawrence Goldberg, T. Gosnell, and S. Sinha, 1990, "Margin Requirements in Futures Markets: Their Relationship to Price Volatility," *Journal of Futures Markets*, 10, 5, 541-554.

[16] Froot, Kenneth A. and Paul G. J. O'Connell, 1999, "The Pricing of US Catastrophe Reinsurance," in *The Financing of Catastrophe Risk*, ed. K. Froot, Chicago: University of Chicago Press, 195-232.

[17] Gabaix, Xavier, Arvind Krishnamurthy, and Olivier Vigneron, 2004, "Limits to Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market," Working paper, MIT.

[18] Gemmill, Gordon and Dylan C. Thomas, 2002, "Noise Trading, Costly Arbitrage, and Asset Prices: Evidence from Closed-End Funds," *Journal of Finance*, LVII, 6, December, 2571-2594.

[19] Goetzmann, William N. and Alok Kumar, 2004, "Diversification Decisions of Individual Investors and Asset Prices" Working paper, Yale University.

[20] Goetzmann, William N. and Massimo Massa, 2003, "Disposition Matters: Volume, Volatility and Price Impact of a Behavioral Bias," Working paper, Yale University.

[21] Greenwood, Robin, 2005a, "Short- and Long-Term Demand Curves for Stocks: Theory and Evidence on the Dynamics of Arbitrage," *Journal of Financial Economics.*

[22] Greenwood, Robin, 2005b, "A Cross-Sectional Analysis of the Excess Comovement of Stock Returns," Working Paper, Harvard University.

[23] Griffin, John M., Jeffrey H. Harris, and Selim Topaloglu, 2003, "The Dynamics of Institutional and Individual Trading," *Journal of Finance*, LVIII, 6, December, 2285-2320.

[24] Harris, Lawrence, 2005, Discussion of paper by Kaniel, Saar, and Titman (2004) at 2005 AFA meetings, Philadelphia.

[25] Harris, Lawrence and Eitan Gurel, 1986, "Price and Volume Effects Associated with Changes in the SP500 List: New Evidence for the Existence of Price Pressure," *Journal of Finance*, 41, 4, September, 815-829.

[26] Hegde, Shantaram P. and John B. McDermott, 2003, "The Liquidity Effects of Revisions to the SP500 Index: An Empirical Analysis," *Journal of Financial Markets*, 6, 413-459.

[27] Jackson, Andrew, 2003, "Noise Trader Risk Exists ... But the Noise Traders Are Not Who You Think They Are," Working paper, London Business School.

[28] Jin, Li and Stewart C. Myers, 2005, "R^2 Around the World: New Theory and New Tests," Forthcoming *Journal of Finance*.

[29] Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2004, "Individual Investor Sentiment and Stock Returns," Working paper, Duke University.

[30] Kaul, Aditya, Vikas Mehrotra, and Randall Morck, 2000, "Demand Curves for Stocks *Do* Sope Down: New Evidence from an Index Weights Adjustment," *Journal of Finance*, LII, 893-912.

[31] Kumar, Alok and Charles M.C. Lee, 2004, "Retail Investor Sentiment and Return Comovements," Working paper, Notre Dame University.

[32] Kyle, Albert S., 1985, "Continuous Actions and Insider Trading," *Econometrica*, 53, 6, November, 1315-1335.

[33] Lee, Charles M. C, Andrei Shleifer, and Richard H. Thaler, 1991, "Investor Sentiment and the Closed-End Fund Puzzle," *Journal of Finance*, XLVI, 1, March, 75-109.

[34] Lee, Wayne Y., Christine X. Jiang, and Daniel C. Indro, 2002, "Stock Market Volatility, Excess Returns, and the Role of Investor Sentiment," *Journal of Banking and Finance*, 26, 2277-2299.

[35] Mitchell, Mark, Todd Pulvino, and Erik Stafford, 2004, "Price Pressure Around Mergers," *Journal of Finance*, 59, 1, February, 31-63.

[36] Morck, Randall, Bernard Yeung, Wayne Yu, 2000, "The Information Content of Stock Markets: Why do Emerging Markets Have Synchronous Stock Price Movements?," *Journal of Financial Economics*, 58, 215-260.

[37] Neal, Robert and Simon M. Wheatley, 1998, "Do Measures of Investor Sentiment Predict Returns?" *Journal of Financial and Quantitative Analysis*, 33, 4, December, 523-547.

[38] Pastor, Lubos and Robert F. Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111, 3, 642-685.

[39] Porter, R. Burt, 2003, "Measuring Market Liquidity," Working paper, University of Florida.

[40] Sadka, Ronnie, 2004, "Liquidity Risk and Asset Pricing," Working paper, University of Washington.

[41] Shleifer, Andrei, 1986, "Do Demand Curves for Stocks Slope Down?" *Journal of Finance*, 41, 3, July, 579-590.

[42] Shleifer, Andrei and Lawrence H. Summers, 1990, "The Noise Trader Approach to Finance," *Journal of Economic Perspectives*, 4, 2, Spring, 19-33.

[43] Shleifer, Andrei and Robert W. Vishny, 1997, "The limits of arbitrage", *Journal of Finance*, 52, 1, March, 35-55.

[44] Sias, Richard W., Laura T. Starks, and Sha M. Tinic, 2001, "Is Noise Trader Risk Priced?" *Journal Financial Research*, XXIV, 3, Fall, 311-329.

[45] Stahel, Christof W., 2003, "Is There a Global Liquidity Factor," Working paper, Ohio State University.

[46] Wang, Ashley W., 2003, "Institutional Equity Flows, Liquidity Risk and Asset Pricing," Working paper, University of California Irvine.

[47] Wurgler, Jeffrey and Ekaterina Zhuravskaya, 2002, "Does Arbitrage Flatten Demand Curves for Stocks?" *Journal of Business*, 75, 4, 583-608.

Figure 1
Market Price Index

This figure shows the price of the market index. The price has been normalized to start at 100 at the beginning of January 1994. Our sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Figure 2
Our Sample of Uninformed Holdings Over Time

This figure shows the average fraction of a company's shares held by uninformed investors. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $H_{EW,t}$ is an equal-weighted average of $H_{i,t}$ across stocks at each point of time. Construction of these measures is described in the text. The graph shows $H_{EW,t}$ for two samples. The full sample contains 608 firms. The subsample contains 131 firms and is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

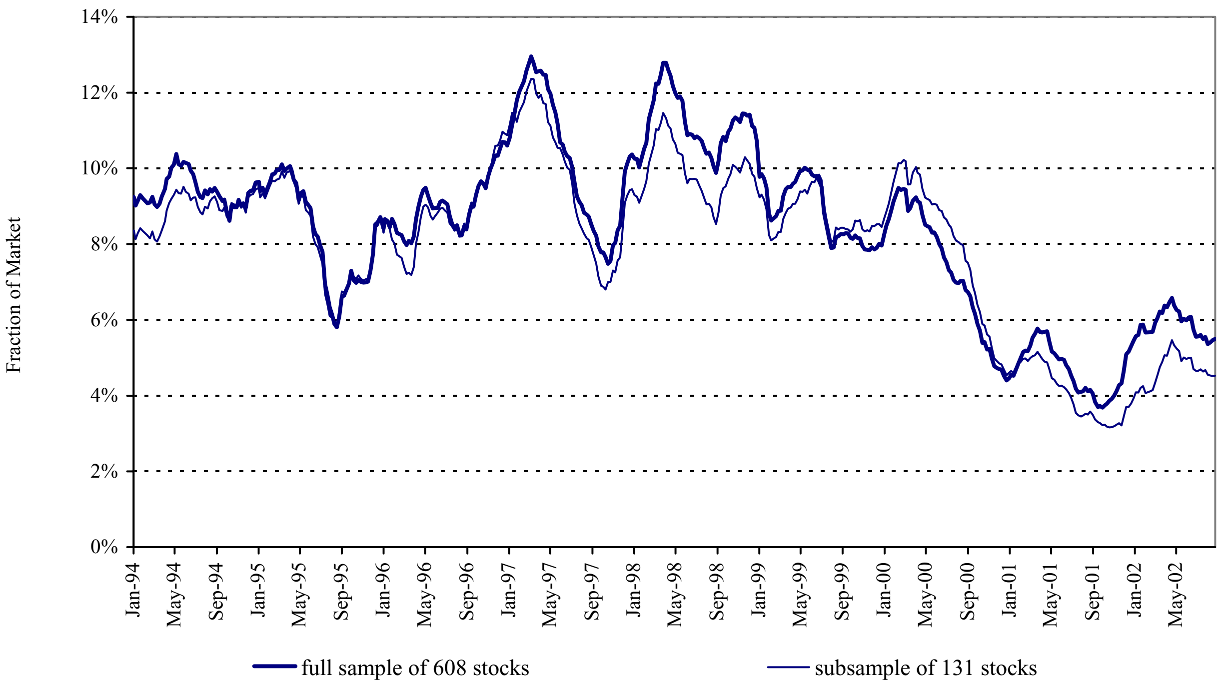


Figure 3
Trading Shocks and Contemporaneous Returns

This figure shows pooled regressions of contemporaneous returns on uninformed net trades. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$ which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured either over a day or a week. Construction of these measures is described in the text. This figure reports results for a subsample of 131 firms as described in the text. T-statistics for the slope coefficient of the linear regression are displayed and allow for clustering across contemporaneous observations. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Y-axis: this period's return ($r_{i,t}$)
X-axis: this period's change in long margin holdings ($\Delta H_{i,t}$)

Panel A: Daily	Panel B: Weekly
t-stat of linear: 44.65	***t-stat of linear: 17.83***

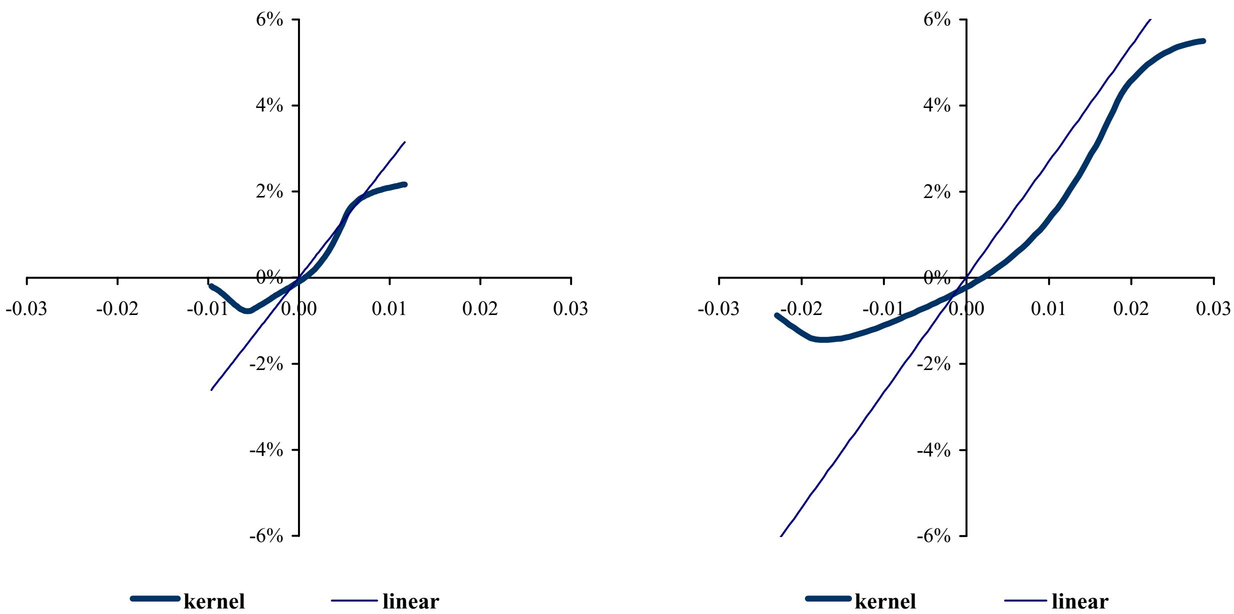
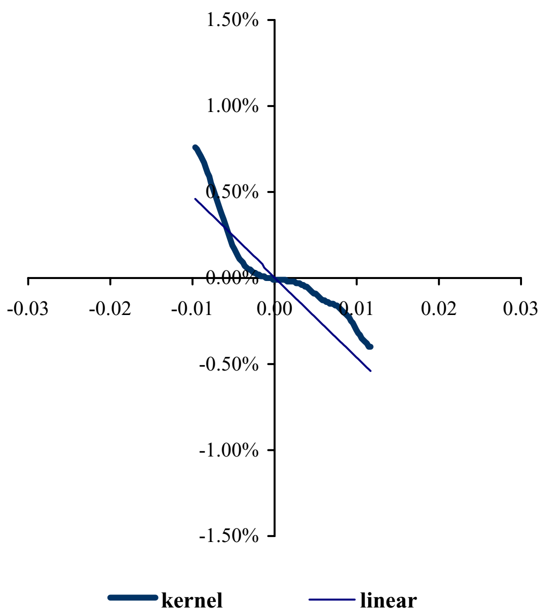


Figure 4
Trading Shocks and Future (Next Period) Returns

This figure shows pooled regressions of future returns on this period's uninformed net trades. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i," divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured either over a day or a week. Construction of these measures is described in the text. This figure reports results for a subsample of 131 firms as described in the text. T-statistics for the slope coefficient of the linear regression are displayed and allow for clustering across contemporaneous observations. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Y-axis: next period's return ($r_{i,t+1}$)
X-axis: this period's change in long margin holdings ($\Delta H_{i,t}$)

Panel A: Daily
t-stat of linear: -8.65



Panel B: Weekly
t-stat of linear: -3.13

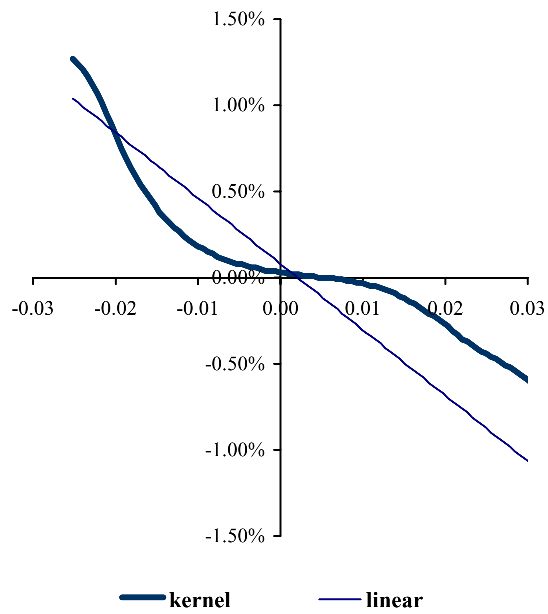
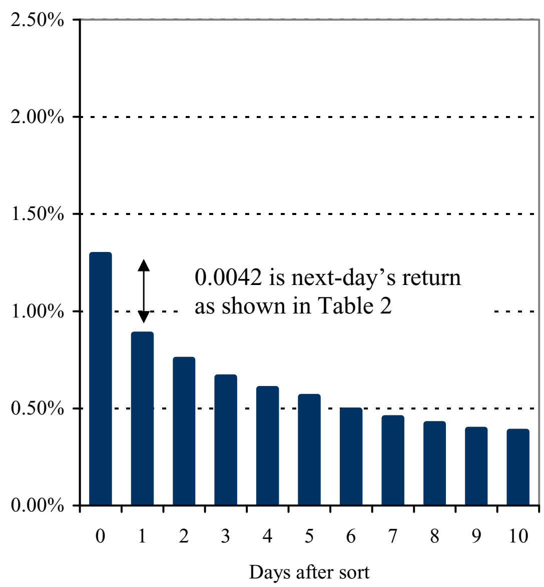


Figure 5
Cumulative Future Returns of the Zero-Cost Portfolio (Inverted)

This figure shows changes to the price of the (inverted) zero-cost portfolio at the time of formation and during the following periods. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured either over a day or a week. Construction of these measures is described in the text. Shares are sorted at time zero into ten deciles based on $\Delta H_{i,t}$. The long short portfolio is long shares in the lowest decile of $\Delta H_{i,t}$ and short shares in the highest decile. This figure reports results for a subsample of 131 firms as described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Panel A: Daily



Panel B: Weekly

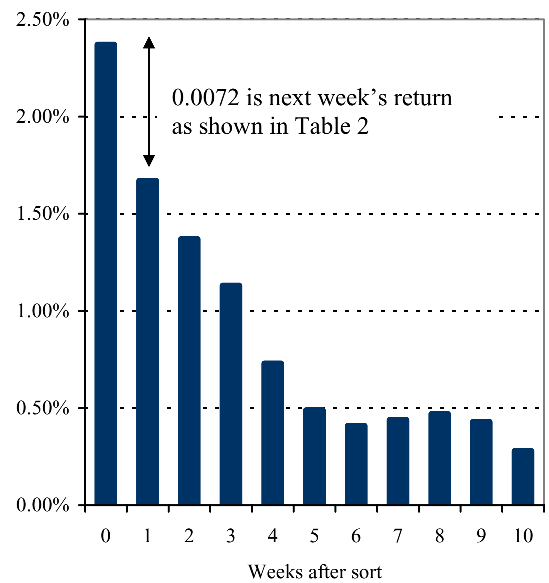


Figure 6
Principal Component Analysis

This figure shows the first twenty-five principal components of uninformed net trading across stocks. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured over a week. $\%\Delta H_{i,t}$ is shares held long on margin this week over shares held long on margin last week (minus one). Construction of these measures is described in the text. Principal components are extracted from the correlation matrix of $\%\Delta H_{i,t}$ and $\Delta H_{i,t}$ using the 131 firm subsample as described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

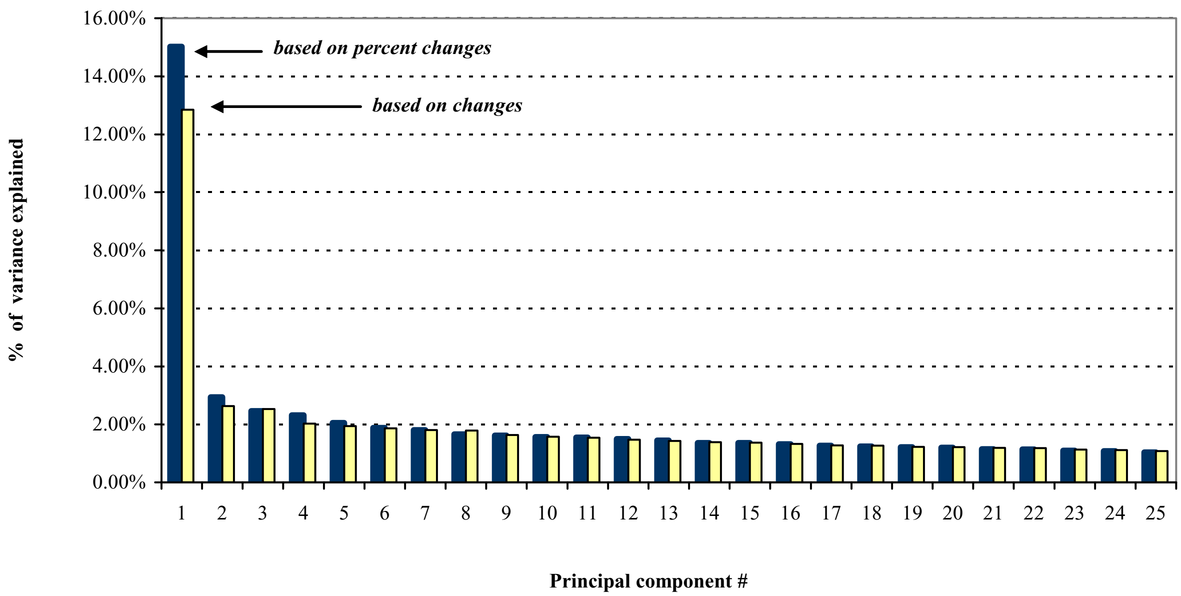
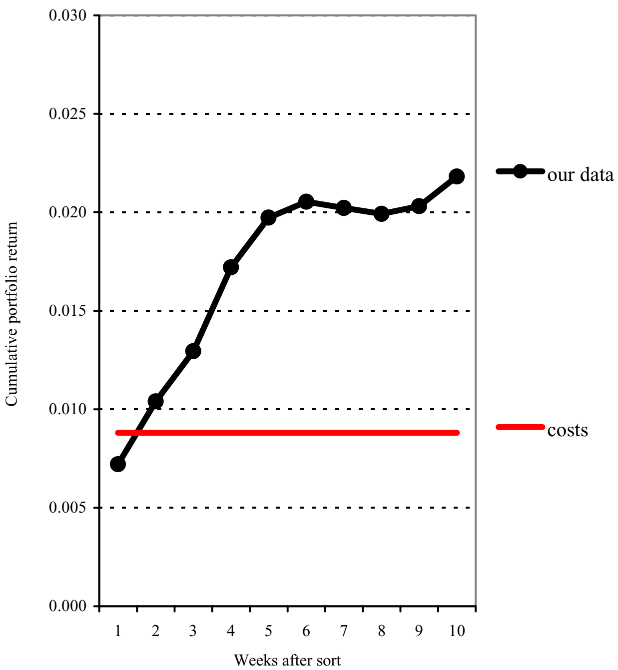


Figure 7
Limits to Arbitrage

This figure shows the cumulative return of the zero-cost portfolio during the ten weeks following formation. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured over a week. Construction of these measures is described in the text. Shares are sorted at time zero into ten deciles based on $\Delta H_{i,t}$. The zero cost portfolio is long shares in the lowest decile of $\Delta H_{i,t}$ and short shares n the highest decile. This figure reports results for a subsample of 131 firms as described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Panel A: Transaction costs



Panel B: After-cost Sharpe ratios

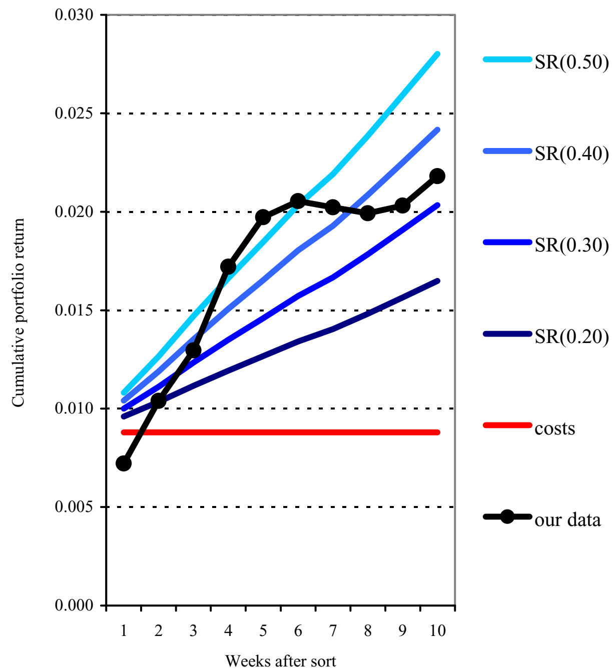


Table 1
Descriptive Statistics of Trading Shocks

This table gives descriptive statistics of aggregate holdings in our sample at the individual stock level. In order to compare holdings and changes in holdings across stocks we use three measures: $H_{i,t}$ is shares held long on margin for stock "i," divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured either over a day or a week. $\%\Delta H_{i,t}$ is shares held long on margin this period over shares held long on margin last period (minus one). Construction of these measures is described in the text. This table also reports the absolute value of some measures. The full sample contains 608 firms. The subsample contains 131 firms and is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Panel A: Cross-sectional measures of $\Delta H_{i,t}$ (i.e., of company time series data)

	Daily					*Weekly*				
	$H_{i,t}$	$\Delta H_{i,t}$	$\lvert \Delta H_{i,t} \rvert$	$\%\Delta H_{i,t}$	$\lvert \%\Delta H_{i,t} \rvert$	$H_{i,t}$	$\Delta H_{i,t}$	$\lvert \Delta H_{i,t} \rvert$	$\%\Delta H_{i,t}$	$\lvert \%\Delta H_{i,t} \rvert$
Full sample										
Average	0.0725	0.0001	0.0013	0.0040	0.0237	0.0721	0.0003	0.0039	0.0194	0.0738
25th-tile	0.0360	0.0000	0.0007	0.0003	0.0155	0.0361	-0.0001	0.0023	0.0029	0.0499
50th-tile	0.0688	0.0000	0.0012	0.0018	0.0201	0.0686	0.0001	0.0037	0.0099	0.0628
75th-tile	0.1049	0.0001	0.0018	0.0051	0.0284	0.1037	0.0004	0.0054	0.0263	0.0852
N	*608*	*608*	*608*	*608*	*608*	*608*	*607*	*607*	*607*	*607*
Subsample										
Average	0.0810	0.0000	0.0012	0.0003	0.0166	0.0801	-0.0001	0.0036	0.0028	0.0511
25th-tile	0.0429	0.0000	0.0007	0.0000	0.0139	0.0426	-0.0001	0.0021	0.0016	0.0439
50th-tile	0.0782	0.0000	0.0011	0.0004	0.0161	0.0773	-0.0001	0.0035	0.0032	0.0496
75th-tile	0.1124	0.0000	0.0016	0.0007	0.0186	0.1101	0.0000	0.0048	0.0051	0.0574
N	*131*	*131*	*131*	*131*	*131*	*131*	*131*	*131*	*131*	*131*

Panel B: Time-series measures from an equally weighted measure ($\Delta H_{EW,t}$)

	Daily					*Weekly*				
	$H_{EW,t}$	$\Delta H_{EW,t}$	$\lvert \Delta H_{EW,t} \rvert$	$\%\Delta H_{EW,t}$	$\lvert \%\Delta H_{EW,t} \rvert$	$H_{EW,t}$	$\Delta H_{EW,t}$	$\lvert \Delta H_{EW,t} \rvert$	$\%\Delta H_{EW,t}$	$\lvert \%\Delta H_{EW,t} \rvert$
Full sample										
Average	0.0850	0.0000	0.0014	0.0014	0.0191	0.0841	0.0001	0.0042	0.0090	0.0615
Stdev.	0.0216	0.0005	0.0005	0.0072	0.0064	0.0220	0.0019	0.0015	0.0296	0.0204
T	*2360*	*2359*	*2359*	*2359*	*2359*	*443*	*442*	*442*	*442*	*442*
Subsample										
Average	0.0810	0.0000	0.0012	0.0003	0.0166	0.0801	-0.0001	0.0036	0.0028	0.0511
Stdev.	0.0214	0.0005	0.0005	0.0076	0.0067	0.0220	0.0019	0.0015	0.0298	0.0199
T	*2360*	*2359*	*2359*	*2359*	*2359*	*443*	*442*	*442*	*442*	*442*

Table 2
Sort Results

This table shows the results of a sorting procedure based on uninformed trading. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured either over a day or a week. Construction of these measures is described in the text. Each period (day or week) we sort stocks into ten deciles based on the increase in aggregate long margin holdings. The full sample contains 608 firms. The subsample contains 131 firms and is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal. T-statistics are based on standard errors that are robust to heteroskedasticity and autocorrelation.

	Full sample: 608 firms				*Subsample: 131 firms*			
	Daily		*Weekly*		*Daily*		*Weekly*	
current period decile	**Next period return**	***stdev***	**Next period return**	***stdev***	**Next period return**	***stdev***	**Next period return**	***stdev***
(lowest $\Delta H_{i,t}$) 1	0.0019	*0.0189*	0.0029	*0.0479*	0.0022	*0.0195*	0.0039	*0.0475*
2	0.0004	*0.0173*	0.0018	*0.0441*	0.0008	*0.018*	0.0027	*0.0439*
3	0.0003	*0.0163*	0.0025	*0.0408*	0.0006	*0.0172*	0.0018	*0.0414*
4	0.0001	*0.0156*	0.0008	*0.0394*	0.0005	*0.0168*	0.0008	*0.04*
5	0.0002	*0.0151*	0.0011	*0.0387*	0.0001	*0.0164*	0.0001	*0.0408*
6	-0.0002	*0.0146*	-0.0002	*0.0371*	-0.0001	*0.0161*	0.0001	*0.0383*
7	-0.0004	*0.0146*	-0.0003	*0.0382*	-0.0003	*0.0164*	-0.0002	*0.0411*
8	-0.0004	*0.0154*	-0.0004	*0.0401*	-0.0005	*0.0166*	0.0004	*0.0432*
9	-0.0007	*0.0168*	-0.0012	*0.0422*	-0.0008	*0.0177*	-0.0006	*0.0431*
(highest $\Delta H_{i,t}$) 10	-0.0013	*0.0183*	-0.0025	*0.0477*	-0.0019	*0.0189*	-0.0033	*0.0462*
zero-cost portfolio								
difference 1-10	0.0032	*0.0089*	0.0055	*0.0226*	0.0042	*0.0118*	0.0072	*0.0288*
t-stat	*16.80*		*5.08*		*16.77*		*5.24*	
N	*2358*		*441*		*2358*		*441*	

7

Table 3
Risk-Adjusted Returns

Returns of our zero-cost portfolio (called "r_1 - r_{10}" and based on uninformed trading) are regressed on the market's return and other factors' returns. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured over a week. Construction of these measures, the size factor (SMB), the market-to-book factor (HML), and the momentum factor (MOM) are all described in the text. Results are based on the subsample of 131 firms that is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

$$r_{1-10,t} = \alpha + \beta_{MKT}\left(r_{m,t} - r_{f,t}\right) + \beta_{SMB} r_{SMB,t} + \beta_{HML} r_{HML,t} + \beta_{MOM} r_{MOM,t} + \varepsilon_t$$

	Reg #1	**Reg #2**	**Reg #3**	**Reg #4**	**Reg #5**
Constant (α)	0.0073	0.0074	0.0073	0.0080	0.0079
(t-stat)	*(5.27)*	*(5.39)*	*(5.20)*	*(6.14)*	*(6.04)*
Market (β_{MKT})	0.0499				0.0185
(t-stat)	*(1.32)*				*(0.49)*
SMB (β_{SMB})		-0.0191			0.0028
(t-stat)		*(-0.82)*			*(0.10)*
HML (β_{HML})			-0.0094		0.0026
(t-stat)			*(-0.52)*		*(0.14)*
MOM (β_{MOM})				-0.1346	-0.1340
(t-stat)				*(-6.54)*	*(-6.60)*
Std. errs	*White*	*White*	*White*	*White*	*White*
N	*441*	*441*	*441*	*441*	*441*

Table 4
Cross-Stock Trading Shocks

This table shows the relationship between a correlation coefficient and a regression coefficient. For each pair of stocks "i" and "j" we make two measurements. The correlation coefficient ($\rho_{i,j}$) measures how trading shocks of "i" and "j" move together. The regression coefficient ($\gamma_{i,j}$) measures the impact that trading in stock "j" has on the returns of stock "i". The regression coefficient is estimated from three different specifications The sample contains the 131 firms for which we have a balanced panel and is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

$$\rho_{i,j} = corr\left(\Delta H_{i,t}, \Delta H_{j,t}\right)$$

$$\gamma_{i,j} = \text{Regression Coefficient}$$

Specification	Regression Used to Generate ($\gamma_{i,j}$)	Corr($\rho_{i,j}$, $\gamma_{i,j}$)	Number of Pairs
1	$r_{i,t} = \alpha + \gamma_{i,j}\Delta H^S_{j,t} + \varepsilon_t$	0.3974	8,515
2	$r_{i,t} = \alpha + \gamma_{ii}\Delta H_{i,t} + \gamma_{ij}\Delta H_{j,t} + \varepsilon_t$	0.1339	8,515
3	$r_{i,t} = \alpha + \gamma_{ii}\Delta H^S_{i,t} + \gamma_{ij}\Delta H^S_{j,t} + \varepsilon_t$	0.1473	8,515

Table 5
Loadings on 1st Principal Component

This table shows the correlation of trading shocks (at the individual stock level) with the first principal component. We also so the correlation of individual stock returns and the first principal component. Panel B shows the same correlations with the part of the first principal component that is orthogonal to overall market returns. $\Delta H_{i,t}$ is the change in uniformed holdings of stock "i" during week "t". The stock's return, rit, of stock "i" over week "t". PC_t is the first principal component across the $\Delta H_{i,t}$ in week "t". PC_Orth_t is the orthogonal component of first principal component with respect to the market return in week "t". The sample contains the 131 firms for which we have a balanced panel and is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Panel A: Correlations of Stock-Level $\Delta H_{i,t}$ and $r_{i,t}$ with First Principal Component (PC_t)

	Correlation of $\Delta H_{i,t}$ and PC_t	Correlation of $r_{i,t}$ and PC_t
Average Across Stocks	0.3755	0.4174
Std Dev Across Stocks	0.0963	0.0702
Number of Correlations < 0	0	0
N	131	131

Panel B: Correlations of Stock-Level $\Delta H_{i,t}$ and $r_{i,t}$ with Orthogonal Portion of First Principal Component (PC_Orthog_t)

	Correlation of $\Delta H_{i,t}$ and PC_Orth_t	Correlation of $r_{i,t}$ and PC_Orth_t
Average Across Stocks	0.3093	0.1374
Std Dev Across Stocks	0.0880	0.1006
Number of Correlations < 0	0	14
N	131	131

Table 6
Market-Wide Shocks

This table reports regression coefficients from pooled regressions of individual stock returns ($r_{i,t}$) on individual stock trading shocks ($\Delta H_{i,t}$). In Regression 2, we include a signed squared term (in units of 100) to take into account any non-linearity in the relationship. We also interact the trading shock with an indicator variable ($I\ mkt_{i,t}$) designed to represent times when the whole market faces large buy or sell imbalances. The indicator variable takes a value of one if the trading shock is positive, the market-wide measure ($\Delta H_{EW,t}$) of trading shocks is positive, and the market-wide measure is in the top 25% of its empirical distribution. The indicator variable can also take a value of one if the trading shock is negative, the market-wide measure ($\Delta H_{EW,t}$) of trading shocks is negative, and the market-wide measure is in the bottom 25% of its empirical distribution. This figure reports results for a subsample of 131 firms as described in the text. T-statistics are displayed and allow for clustering across contemporaneous observations. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

$$r_{i,t} = \gamma_1 + \gamma_2\left(\Delta H_{i,t}\right) + \gamma_3\left(\Delta H_{i,t} \cdot I_{i,t}^{mkt}\right) + \gamma_4\left(sign\left|\Delta H_{i,t}\right|^2\right) + \varepsilon_{i,t}$$

	Reg. 1	**Reg. 2**	**Reg. 3**
γ_1	0.0002	0.0010	0.0006
t-stat	*(0.12)*	*(0.61)*	*(0.40)*
γ_2	2.6843	4.9693	3.1599
t-stat	*(17.83)*	*(15.85)*	*(14.95)*
γ_3			4.1249
t-stat			*(11.32)*
γ_4		-1.4340	-1.5893
t-stat		*(-10.94)*	*(-11.79_*
N. obs	57,902	57,902	57,902

Table 7
Co-Movement

This table reports the average R^2 from regressions of individual stock returns on factors. We consider each of the 131 firms for which we have a balanced panel. Individual stock returns are labeled $r_{i,t}$. Factors include: the market return ($r_{m,t}$); the portion of the market return that is orthogonal to trading shocks (r orthog $_{m,t}$); a market-wide, equal-weighted index of trading shocks ($\Delta H_{EW,t}$); and trading shocks in the particular stock ($\Delta H_{i,t}$). The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Specification	Regression Used to Generate R^2 Measure	Average R^2	Stdev of R^2	Num. Stocks
1	$r_{i,t} = \alpha + \beta_m(r_{m,t}) + \varepsilon_t$	0.2958	0.0945	131
2	$r_{i,t} = \alpha + \beta_O(r_{m,t}^{Orthog}) + \varepsilon_t$	0.1630	0.0905	131
3	$r_{i,t} = \alpha + \beta_E(\Delta H_{EW,t}) + \varepsilon_t$	0.1582	0.0495	131
4	$r_{i,t} = \alpha + \beta_O(r_{m,t}^{Orthog}) + \beta_E(\Delta H_{EW,t}) + \varepsilon_t$	0.3212	0.0865	131
5	$r_{i,t} = \alpha + \beta_i(\Delta H_{i,t}) + \varepsilon_t$	0.0827	0.0624	131
6	$r_{i,t} = \alpha + \beta_E(\Delta H_{EW,t}) + \beta_i(\Delta H_{i,t}) + \varepsilon_t$	0.1889	0.0603	131
7	$r_{i,t} = \alpha + \beta_O(r_{m,t}^{Orthog}) + \beta_E(\Delta H_{EW,t}) + \beta_i(\Delta H_{i,t}) + \varepsilon_t$	0.3474	0.0911	131

Appendix 1: Theoretical Model

Equilibrium: Substitute the price conjecture in the definition of Q_{t+1} to get:

$$Q_{t+1} = -(R-1)(q_0 + q_z\overline{Z}) - q_z(R-\alpha_z)(Z_t - \overline{Z}) + \frac{R}{R-\alpha_D}\varepsilon_{D,t+1} + \frac{1}{R-\alpha_D}S_{t+1} + q_z u_{z,t+1}$$

Compute conditional moments and substitute in the market clearing equation to get:

$$1 = \omega\frac{-(R-1)(q_0 + q_z\overline{Z}) - q_z(R-\alpha_z)(Z_t - \overline{Z})}{a\sigma_Q^2} + (1-\omega)Z_t$$

The equation directly above yields two conditions (one for the stochastic component and one for the non-stochastic component):

$$-\omega(R-1)(q_0 + q_z\overline{Z}) = a\sigma_Q^2\left((1-\omega)\overline{Z} - 1\right) \quad (1)$$

$$q_z(R-\alpha_z)\omega = (1-\omega)a\sigma_Q^2 \quad (2)$$

Solve equation (2) and choose the root with the following behavior in the limit: $(\sigma_F^2 \to 0)$ implies $(q_z \to 0)$. This yields an equilibrium if $(2a(1-\omega))^2\sigma_F^2\sigma_u^2 \leq 1$:

$$q_z = \frac{\omega}{2a(1-\omega)} \cdot \frac{R-\alpha_z}{\sigma_u^2}\left[1 - \sqrt{1 - (2a(1-\omega))^2\sigma_F^2\sigma_u^2}\right]$$

Contemporaneous Correlation:

$$\begin{aligned} Cov(\Delta\aleph_t, Q_t) &= (1-\omega)q_z \cdot Cov(Z_t - RZ_{t-1}, Z_t - Z_{t-1}) \\ &= (1-\omega)q_z(1+R)\left(\frac{\sigma_u^2}{1-\alpha_z^2}\right)(1-\alpha_z) > 0 \end{aligned}$$

$$\begin{aligned} Cov(\%\Delta\aleph_t, Q_t) &= -q_z(R-\alpha_z) \cdot Cov\left(Z_{t-1}, \frac{Z_t}{Z_{t-1}}\right) + q_z \cdot Cov\left(u_{z,t}, \frac{Z_t}{Z_{t-1}}\right) \\ &= -q_z(R-\alpha_z)\left\{E\left[\frac{1}{Z_{t-1}}\right]Cov(Z_{t-1}, Z_t) + E\left[\frac{-Z_t}{Z_{t-1}^2}\right]Cov(Z_{t-1}, Z_{t-1})\right\} \\ &= q_z\frac{\sigma_u^2}{1-\alpha_z^2}\left\{(R-\alpha_z)\left(E\left[\frac{Z_t}{Z_{t-1}^2}\right] - \alpha_z E\left[\frac{1}{Z_{t-1}}\right]\right) + (1-\alpha_z)E\left[\frac{1}{Z_{t-1}}\right]\right\} \\ &= q_z\frac{\sigma_u^2}{1-\alpha_z^2}\left((R-\alpha_z) \cdot g\left(\overline{Z}, \alpha_z, \sigma_u^2\right) + (1-\alpha_z)E\left[\frac{1}{Z_{t-1}}\right]\right) > 0 \end{aligned}$$

Covariance with Future Returns:

$$
\begin{aligned}
Cov\left(\Delta\aleph_t, Q_{t+1}\right) &= -(1-\omega)q_z\left(R-\alpha_z\right)\cdot Cov\left(Z_{t+j-1}, Z_t - Z_{t-1}\right) \\
&= -(1-\omega)q_z(R-\alpha_z)\left(\frac{\sigma_u^2}{1-\alpha_Z^2}\right)\left(1-\alpha_z\right)\alpha_z^j \\
Cov\left(\%\Delta\aleph_t, Q_{t+1}\right) &= -q_z\left(R-\alpha_z\right)\cdot Cov\left(Z_{t+j-1}, \frac{Z_t}{Z_{t-1}}\right) \\
&= -q_z\left(R-\alpha_z\right)\left\{E\left[\frac{1}{Z_{t-1}}\right]Cov\left(Z_{t+j-1}, Z_t\right) + E\left[\frac{-Z_t}{Z_{t-1}^2}\right]Cov\left(Z_{t+j-1}, Z_{t-1}\right)\right\} \\
&= -q_z\left(R-\alpha_z\right)\left\{E\left[\frac{1}{Z_{t-1}}\right] - \alpha_z E\left[\frac{Z_t}{Z_{t-1}^2}\right]\right\}\frac{\sigma_u^2}{(1-\alpha_z^2)}\alpha_z^{j-1} \\
&= -q_z\left(R-\alpha_z\right)\frac{\sigma_u^2}{(1-\alpha_z^2)}\cdot g\left(\overline{Z}, \alpha_z, \sigma_u^2\right)\alpha_z^{j-1} < 0
\end{aligned}
$$

Two Asset Model:

There is no closed-form solution of the two asset model. For Stock A, we obtain two equations with two unknown parameters. For notational purposes, set $q_{AA} = q_z^{AA}$ and $q_{BA} = q_z^{BA}$. The coefficient q_{AA} relates the uninformed trading in Stock A to the price of Stock A. The coefficient q_{BA} relates trading in Stock B to the price of Stock A. Note that a is the risk aversion coefficient of the optimizing agents; M is the ratio of the variance between the dividend of Stock A and the uninformed trading shocks to Stock A; K is also a constant:

$$
0 = 2\rho\cdot q_{AA}^3 a q_{BA}^2 + (4-a)q_{AA}^2 q_{BA} + 2\rho\cdot(1-a)q_{AA}q_{BA}^2 aMq_{BA}
$$

$$
\begin{gathered}
0 = -K\left(2\rho\cdot q_{BA}^3 a q_{AA}^3 + (4-a)q_{BA}^2 q_{AA} + 2\rho\cdot(1-a)q_{BA}q_{AA}^2 aMq_{AA}\right) - \\
a^2\left(M + q_{AA}^2 + q_{BA}^2 + 2\rho\cdot q_{AA}q_{BA}\right)^2 - 4\left(\rho\left(q_{AA}^2 + q_{BA}^2\right) + 2q_{AA}q_{BA}\right)^2
\end{gathered}
$$

We can show there is a positive price impact on Stock A from trading in Stock B. In other words, $q_{BA} > 0$. A similar set of equations is obtained for Stock B with $q_{AB} > 0$. [Additional equations to be provided.]

Appendix 2: Subsample selection

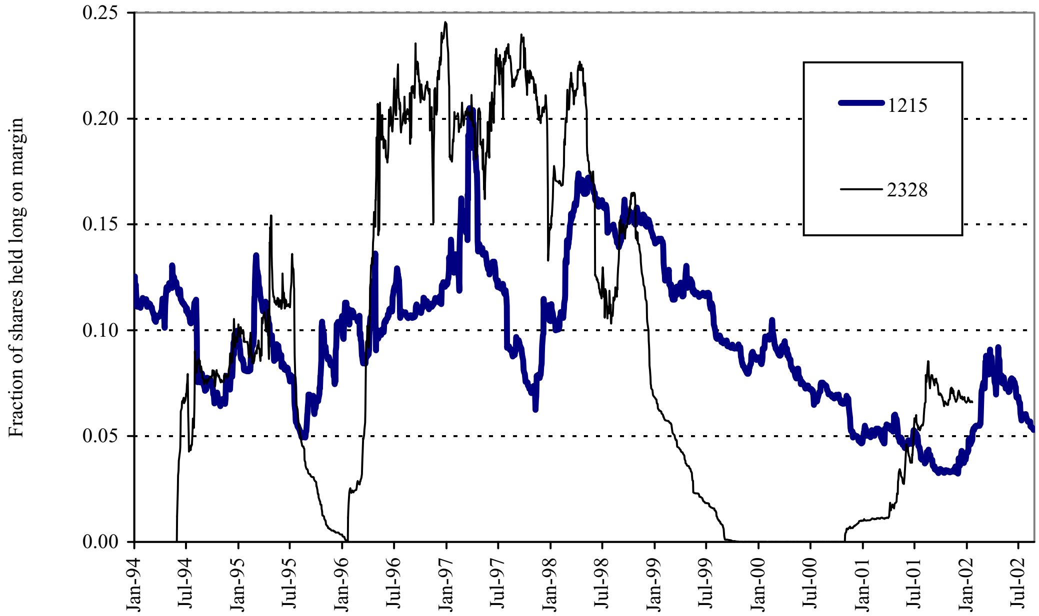
Not all stocks in Taiwan are actively held on margin. Some stocks have stock price information when they enter our sample, but do not have any shares held on margin. At a later time, stocks begin to be held on margin. There is a "build-up period" as holdings go from zero shares to some steady-state level. During the build-up period, the level of margin holdings increases in a predictable fashion until it reaches a steady state. Other stocks in our sample see margin holdings disappear during the sample period. There is a "wind-down period" in which the level of margin holdings decreases in a predictable fashion. Finally, there are stocks where the number of shares held on margin does not change very often.

The graph below shows the level of margin holdings for two individual stocks. The first stock is ticker 1215 and has non-zero margin holdings throughout our sample period. Notice that the level of holdings looks fairly similar to the average level of holdings shown in Figure 1. The second stock in the graph below is ticker 2328. This stock has no margin holdings until June 1994. At that time, margin holdings build up rapidly until they reach a similar level to other stocks. There is wind-down period before January 1996, followed by a very quick rise to more normal levels. For most of 1999, margin holdings decline until they hit zero. Between June 2000 and June 2001, there are no holdings data for ticker 2328. After June 2001, margin holdings again build up until they reach levels that are commensurate with the rest of the market. In early 2002 we cease to have margins holding data for ticker 2328 although price data continue.

The TSE has two situations that lead to a predictable trend in the level of margin holdings. The first is when there is a capital change by a firm; the second is when a firm reports poor operating performance. Either situation can cause the TSE to declare that all long margin positions must be closed out. It is around such episodes that margin holdings act predictably. For the reasons discussed above and shown in the graph below, we run many of our tests on a subsample of companies with positive margin holdings for the entire time the stock is listed. There are 141 such companies. To run the two-pass regressions on individual assets, it makes sense to have a balanced panel of data. We therefore restrict the subsample to those companies with data throughout our sample period. The second restriction eliminates ten companies, leaving us with a subsample of 131 stocks. We carry out all tests with the full sample of 608 firms as well as the subsample of 131 firms. Many of our tests involve zero-cost portfolios so differences when using one subsample instead of the main sample of 608 firms are minimized.

Appendix 2 (continued)
Holdings for Two Individual Stocks

This figure shows the fraction of two companies' shares from our sample. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. Construction of this measures is described in the text. The first company (ticker=1215) has positive holdings for the entire time it is listed. The second stock (ticker=2328) has a one-year period where holdings in our sample disappear completely from the data (the stock is no longer held on margin). This period is from 1999 to 2000. Thus, ticker 1215 is included in our balanced panel (subsample of 131 companies) and stock 2328 is not. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.



Appendix 3: Additional Notes on Identification

The net trades of an entire market are zero by definition. Thus, studying the trading behavior of investors can be problematic, especially when using large samples that are representative of all investors. One way around such problems is to use micro-structure data and order flow data. Another approach is to try to infer behavior from the net trades of a well defined subsample of investors.

Comparison with the Barber and Odean dataset: Our identification of individual investors is both comparable to, and different from, recent work on investment behavior. For example, work by Barber and Odean (2000), Goetzmann and Massa (2003), Kumar and Lee (2004), and Goetzmann and Kumar (2004) study a subset of individual investors who use a certain discount broker. These authors only observe an individual's holdings with that brokerage firm, but not holdings held in other types of accounts or with other brokers. Such censored observations, however, pose no problem for economic research. The sample of investors is well defined and is (most probably) representative of the larger universe of individual investors who use discount brokers. What's more, results of these studies give us a starting point for thinking about similar groups of investors, such as those who use full service brokers or those who engage in internet trading.[1]

Our sample of data allows us to observe all holdings bought with money borrowed from a broker, but not other equity holdings. We do not, for example, see holdings bought with cash. Nor do we see holdings from those individuals to whom brokers would not lend. This is not a problem since this paper does not try to infer the trading behavior of the average individual investor. Instead, the dataset simply tests whether individual investors move prices and/or if their presence affects equilibrium-expected returns.

Comparison with closed-end fund studies: Our identification of individual investors is both comparable to, and different from, recent work on the closed-end fund premium and discount. Some papers that look at closed-end fund premiums/discounts attempt to use these premiums/discounts as a measure of investor sentiment. Implicitly these studies can only measure the sentiment of investors who trade closed-end fund shares. But since closed-end fund shares are typically bought and sold by individual investors, the premiums/discounts are typically thought of as a measure of individual investor sentiment. One does not need the complete holdings of individual investors to carry out this line of research, much as we do not need all trades by the individuals who use margin accounts.

[1] Barber and Odean have completed numerous studies, some of which examine these other groups.

Other: Some readers worry that we do not have the complete universe of uninformed trades and this affects results (though it is not clear if our results would be strengthened or weakened). Some readers worry that investors in our sample could be placing counter-balancing trades. We see such worries, while potentially interesting research topics, to be outside the questions this paper is addressing. This paper simply asks if uninformed trades affect asset prices. The paper then asks if the effects are transitory or permanent. We do not try to estimate a price response function.[2] We know that the amount bought and sold on margin is publicly available each day and our tests are based on sort-portfolios formed at the end of each day or week. Therefore, other trades by the same investors is outside our framework. The entire market can condition on the set of trades we examine and the trades we examine are linked to changes in asset prices. Finally, the trades we examine represent a nontrivial portion of the market. This paper does not represent a study of trading that may affect a very, very small fraction of wealth. Instead, we know long margin holdings account for almost 10% of shares outstanding and an even larger fraction of trading volume.

[2]A price response function tries to estimate how much does the price move for every 100,000 dollars (shares, Taiwan dollars, etc.) bought or sold. If we were trying to estimate such a quantity then of course we would need all uninformed trades.

Appendix 4
Expanded Sort Results

This table shows the results of a sorting procedure. In order to compare holdings and changes in holdings across stocks we use $H_{i,t}$, which is defined as shares held long on margin for stock "i" divided by total shares outstanding. $\Delta H_{i,t}$ is the difference in shares held long on margin for stock "i" divided by total shares outstanding measured either over a day or a week. Construction of these measures is described in the text. Each period (day or week) we sort stocks into ten deciles based on the increase in aggregate long margin holdings over the past "J" periods. We then report the per-period return to a zero cost portfolio over the following "K" periods. Thus, the top left number, 0.0032, represents a return of 32bp over a one-day holding period. The full sample contains 608 firms. The subsample contains 131 firms and is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal. T-statistics are based on standard errors corrected for heteroskedasticity and autocorrelation.

Full sample: 608 firms

"J" formation days in the past	*return over next "K" days* 1	2	3
1	0.0032	0.0045	0.0052
	(16.80)	*(15.10)*	*(13.96)*
2	0.0030	0.0043	0.0052
	(15.34)	*(13.09)*	*(11.60)*
3	0.0027	0.0039	0.0047
	(13.88)	*(11.22)*	*(9.63)*

Subsample: 131 firms

"J" formation days in the past	*return over next "K" days* 1	2	3
1	0.0042	0.0055	0.0064
	(16.77)	*(14.18)*	*(13.29)*
2	0.0037	0.0051	0.0061
	(14.84)	*(12.12)*	*(11.04)*
3	0.0033	0.0048	0.0056
	(13.24)	*(11.13)*	*(9.51)*

Full sample: 608 firms

"J" formation weeks in the past	*return over next "K" weeks* 1	2	3
1	0.0055	0.0077	0.0099
	(5.08)	*(4.66)*	*(4.48)*
2	0.0053	0.0088	0.0109
	(4.74)	*(4.68)*	*(4.26)*
3	0.0056	0.0085	0.0115
	(4.94)	*(4.40)*	*(4.17)*

Subsample: 131 firms

"J" formation weeks in the past	*return over next "K" weeks* 1	2	3
1	0.0072	0.0104	0.0130
	(5.24)	*(5.13)*	*(4.92)*
2	0.0066	0.0104	0.0142
	(4.40)	*(4.69)*	*(4.79)*
3	0.0067	0.0117	0.0171
	(4.82)	*(5.18)*	*(5.45)*

Appendix 5: Factor Construction

We construct our own Fama-French size (SMB) and book-to-market (HML) portfolios as well as a Carhart momentum (MOM) portfolio. We do this at both daily and weekly frequencies. After construction, we compare our daily time series to similar time series that were graciously provided by Brad Barber, Neil Yi-Tsung Lee, Yu-Jane Liu, and Anlin Chen. The correlation between our series and theirs is high for SMB and HML. Our MOM series is not highly correlated with Chen's due to the fact that he sorts on the past one-year returns and we sort on past days or week's returns (as we explain below). The test results presented in this paper are at a weekly frequency.

Size portfolio

We construct a zero-cost size portfolio, also known as "small minus big" or "SMB." Each week we sort stocks into deciles based on market capitalization (as of the Friday close). SMB is the return on the portfolio that goes long the bottom 30% of stocks (the smallest three deciles)and short the top 30% of stocks (the largest or biggest three deciles). Portfolios are equally weighted and held for one week.

Market-to-book portfolio

We construct a zero-cost market-to-book portfolio, also known as "high minus low" or "HML." Each week we sort stocks into deciles based on their book-to-market ratios (the market prices are as of the Friday close and the book values are as of the previous December). HML is the return on the portfolio that goes long the top 30% of stocks (the high or top three deciles) and short the bottom 30% of stocks (the low or bottom three deciles.) Portfolios are equally weighted and held for one week.

Momentum portfolio

We construct a zero-cost momentum portfolio, known also as "MOM." Each week we sort stocks into deciles based on the previous week's return (the Friday close to Friday close). MOM is the return on the portfolio that goes long the top 30% of stocks (the winners) and short the bottom 30% of stocks (the losers). Portfolios are equally weighted and held for one week.

Appendix 6
Double Sort: Trading Shocks, Returns, and Turnover

This table shows the results of a sorting procedure. Panel A sorts independently by current returns ($r_{i,t}$) and current trading shocks ($\Delta H_{i,t}$). Panel B sorts independently by current trading volume expressed as turnover ($Turn_{i,t}$) and current trading shocks ($\Delta H_{i,t}$). Results show next period's returns ($r_{i,t+1}$). The subsample contains 131 firms and is described in the text. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

Panel A: Next Week's Return ($r_{i,t+1}$) After an Independent Double-Sort by Trading Shocks and Returns

	Low $\Delta H_{i,t}$	**Medium $\Delta H_{i,t}$**	**High $\Delta H_{i,t}$**	**Effect From $\Delta H_{i,t}$**
Low $r_{i,t}$	0.0017	0.0001	-0.0019	-0.0036
Medium $r_{i,t}$	0.0015	0.0008	-0.0015	-0.0030
High $r_{i,t}$	0.0034	0.0008	-0.0011	-0.0045
Effect From $r_{i,t}$	0.0017	0.0007	0.0008	

Next Week's Return ($r_{i,t+1}$) After an Independent Double-Sort by Trading Shocks and Trading Volume (Turnover)

	Low $\Delta H_{i,t}$	**Medium $\Delta H_{i,t}$**	**High $\Delta H_{i,t}$**	**Effect From $\Delta H_{i,t}$**
Low $Turn_{i,t}$	0.0024	0.0006	-0.0008	-0.0032
Medium $Turn_{i,t}$	0.0011	-0.0001	-0.0003	-0.0014
High $Turn_{i,t}$	0.0031	-0.0001	-0.0020	-0.0051
Effect From $Turn_{i,t}$	0.0007	-0.0007	-0.0012	